Mälardalen University Doctoral Dissertation 275

Increasing energy efficiency in electric trains operation

Driver advisory systems and energy storage

Nima Ghaviha

MÄLARDALEN UNIVERSITY
SWEDEN

Mälardalen University Press Dissertations
No. 275

INCREASING ENERGY EFFICIENCY IN ELECTRIC TRAINS OPERATION

DRIVER ADVISORY SYSTEMS AND ENERGY STORAGE

Nima Ghaviha

2018

MÄLARDALEN UNIVERSITY
SWEDEN

School of Business, Society and Engineering

ISBN 978-91-7485-409-1
ISSN 1651-4238
Printed by E-Print AB, Stockholm, Sweden

Mälardalen University Press Dissertations
No. 275

INCREASING ENERGY EFFICIENCY IN ELECTRIC TRAINS OPERATION
DRIVER ADVISORY SYSTEMS AND ENERGY STORAGE

Nima Ghaviha

Akademisk avhandling

som för avläggande av teknologie doktorsexamen i energi- och miljöteknik vid Akademin för ekonomi, samhälle och teknik kommer att offentligen försvaras fredagen den 16 november 2018, 13.00 i Pi, Mälardalens högskola, Västerås.

Fakultetsopponent: Professor Rob M.P. Goverde, TU Delft

MÄLARDALEN UNIVERSITY
SWEDEN

Akademin för ekonomi, samhälle och teknik

Abstract

Electric traction is the most efficient traction system in the railway transportation. However, due to the expensive infrastructure and high power demand from the grid, the share of electric trains in the railway transportation is still lower than other trains. Two of the possible solutions to increase the share of electric trains are: optimal train operation to minimize energy consumption, the use of batteries as the energy source for driving electric trains on non-electrified lines. This thesis aims to extend the knowledge in the field of energy optimal operation of electric trains and battery-driven electric trains.

Energy optimal operation of electric trains is supervised using a driver advisory system (DAS), which instructs the driver to operate the train in an energy-efficient manner. This thesis contributes to DAS technology under two topics: the increase of energy efficiency and the design of DAS.

This thesis presents a complete procedure of designing a DAS from the mathematical formulation to application on the train. The designed DAS is in the form of an Android application and is based on a dynamic programming approach. The computational performance of the approach is enhanced using heuristic state reducing rules based on the physical constraints of the system. The application of the DAS shows a potential reduction of 28% in energy consumption.

This thesis considers the detailed energy losses in the whole propulsion system using a regression model that is generated from validated physical models. The application of the regression model instead of a previous constant efficiency factor model results in 2.3% reduction in energy consumption of the optimum speed profiles.

Based on the solution for the normal electric trains, a solution is also offered for the optimal operation of battery-driven electric trains, in which the characteristics of the battery as one of the main components are considered using an electrical model. The solution presented in this thesis, is to combine the popular single mass point train model with an electrical circuit battery model.

Furthermore, this thesis evaluates the performance of the optimization approaches and validates the models against the measurements from actual drives of a real-life battery train. The results show a potential of around 30% reduction in the charge consumption of the battery.

The results of this thesis (algorithms and the Android application) are provided as open source for further research in the field of energy efficient train control.

ISBN 978-91-7485-409-1
ISSN 1651-4238

To my family!

Acknowledgement

First I would like express my profound gratitude toward my supervisors Prof. Erik Dahlquist and Prof. Markus Bohlin for their continuous support during the past years. This research would not have been fruitful without their guidance and encouragement. My sincere appreciation to Christer Holmberg, my mentor from Bombardier Transportation; everything I learned in power engineering and electric trains was thanks to his guidance and support. I would also like to thank my co-supervisor Dr. Fredrik Wallin. I am grateful to Magnus Forsen for providing me with the opportunity to work at Bombardier during my PhD and also PPC team at Bombardier Transportation for their help with this research project, namely: Per Bengtsson, David Lindgren, and Kevin Babr. I would also like to thank Dr. Helena Jerregård and Dr. Stig Larsson from RISE SICS Västerås for their support during the STREAM project. Special thanks to Dr. Martin Joborn from RISE SICS for the great discussions and for reviewing this thesis.

I would also like to thank Prof. Kondo from Chiba University that provided me with the opportunity to work in their lab. Further, I am grateful to Prof.Konstantinos Kyprianidis for the opportunity to work with him during the last six months of my PhD studies. Special thanks goes to Dr. Jan Sandberg for reviewing this thesis as well as for the great experiences that I gained during teaching in his courses.

Special thanks to my colleagues and dear friends at EST department for all the inspirational conversations, coffee breaks and lots of happy memories. Thanks to my friends outside university, both in Sweden and Iran, that are very close and dear to me.

Many thanks to Vale for her continuous and unconditional support during the past year. Last but foremost, much appreciation to my parents and my brother, I could not have reached this far in life without their endless support and love.

This research was conducted at the school of Business, Society and Engineering at Mälardalen University, Sweden and was supported financially by EST department at Mälardalen University, and VINNOVA (2014-04319 and 2012-01277) as a part of STREAM project lead by RISE SICS.

Nima Ghaviha
October 2018
Västerås, Sweden

Summary

Electric traction is the most efficient traction system in the railway transportation. However, due to the expensive infrastructure and high power demand from the grid, the share of electric trains in railway transportation is still lower than other trains. Two are the possible solutions to increase the share of electric trains: to optimize electric train operations to minimize the energy consumption and to use batteries as the energy source for driving electric trains on non-electrified lines. This thesis aims to extend the knowledge in the field of energy optimal operation of electric trains and battery-driven electric trains.

Energy optimal operation of electric trains is supervised using a driver advisory system (DAS), which instructs the driver to operate the train in an energy-efficient manner. This thesis contributes to DAS technology under two topics: the increase of energy efficiency and the design of driver advisory systems.

Although there are already DAS systems in use in some railway lines, there are no clear study on the design procedure of such systems. This thesis presents the design procedure of a DAS from the mathematical formulations to the design of the interface. The application of the designed DAS on a real train shows the promising decrease of 28% in energy consumption.

To increase the energy efficiency in the problem of energy optimal train operation, this thesis goes deep to the component level in the propulsion system by considering the detailed power losses in each component. The results of this thesis show that the optimum driving styles generated by considering the detailed power losses are around 2.3% more energy efficient compared to the optimum driving styles generated using one constant efficiency factor for the whole train.

Based on the solution for the normal electric trains, a solution is also offered for the optimal operation of battery-driven electric trains, in which the characteristics of the battery as one of the main components are considered using an electrical model. Furthermore, this thesis validates the models and evaluates the optimization performance against the actual drives of a real-life battery train. The results show a potential of around 30% reduction in the charge consumption of the battery.

The results presented in this thesis can be used as a basis for further research and development in the field of energy optimal operation of electric trains and battery driven electric trains.

Sammanfattning

Elektriska traktionssystem är de mest effektiva traktionssystemen för järnvägsfordon. Pågrund av den kostsamma infrastrukturen och höga krav påeffekt från elnätet är dock andelen eltåg vid järnvägstransporter fortfarande lägre än andra tågtyper. Optimering av tågets manövrering för att minimera energiförbrukningen och användning av batterier som energikälla för att köra eltäg pä icke-elektrifierade linjer är tvåav lösningarna som kan öka andelen eltåg vid järnvägstransporter. Den här Avhandlingen syftar till att utöka kunskapen inom energioptimering av eltåg och batteridriven eltåg.

Energioptimal drift av eltåg övervakas med hjälp av ett Driver Advisory System (DAS), vilket är ett system som instruerar föraren att driva tåget påett energieffektivt sätt. Denna avhandling bidrar till DAS-teknologin inom tvåområden: ökad energieffektivitet och utformning av DAS.

Även om det finns DAS-system som används påvissa järnvägslinjer finns det ingen tydlig studie om designproceduren för sådana system. Den här avhandlingen presenterar designproceduren för en DAS från de matematiska formuleringarna till utformningen av gränssnittet. Verklig tillämpningen av den DAS som designats i anslutning till avhandlingsarbetet visar en lovande minskning av energiförbrukningen med cirka 30%. För att öka energieffektiviteten i koppling till problemet med energioptimal tågets manövrering, går denna avhandling pådjupet rörande komponenter i framdrivningssystemet genom att beakta de detaljerade effektförlusterna för varje komponent. Resultaten av denna avhandling visar att de optimala körstilarna som genereras genom att överväga de detaljerade effektförlusterna är cirka 2,3% mer energieffektiva jämfört med de optimala körstilarna som genereras med en konstant effektivitetsfaktor för hela tåget.

Baserat pålösningen för nätdrivna eltåg, erbjuder avhandlingen ocksåen lösning för optimal drift av batteridrivna eltåg, där batteriets egenskaper som en av huvudkomponenterna beaktas med hjälp av en elektrisk modell. Dessutom validerar denna avhandling modeller och utvärderar den framtagna optimeringsmetoden mot mätningar påett verkligt batteridrivet eltåg. Resultaten visar potential för cirka 30% minskning av batteriets energiförbrukning.

Resultaten som presenteras i denna avhandling kan användas som underlag för vidare forskning och utveckling inom området energioptimal drift av nätdrivna och batteridrivna eltåg.

List of Papers

This thesis is based on the following papers, which are referred to in the text by their Roman numerals.

I Ghaviha, N., Bohlin, M., Wallin, F., & Dahlquist, E. (2015, November). Optimal Control of an EMU Using Dynamic Programming and Tractive Effort as the Control Variable. In Proceedings of the 56th Conference on Simulation and Modelling (SIMS 56), October, 7-9, 2015, Linköping University, Sweden (No. 119, pp. 377-382). Linköping University Electronic Press.

II Ghaviha, N., Bohlin, M., & Dahlquist, E. (2016, June). Speed profile optimization of an electric train with on-board energy storage and continuous tractive effort. In Power Electronics, Electrical Drives, Automation and Motion (SPEEDAM), 2016 International Symposium on (pp. 639-644). IEEE.

III Ghaviha, N., Campillo, J., Bohlin, M., & Dahlquist, E. (2017). Review of application of energy storage devices in railway transportation. Energy Procedia, 105, 4561-4568.

IV Ghaviha, N., Holmberg, C., Bohlin, M., & Dahlquist, E. (2017). Modeling of Losses in the Motor Converter Module of Electric Multiple Units for Dynamic Simulation Purposes. Energy Procedia, 142, 2303-2309.

V Ghaviha, N., Bohlin, M., Holmberg, C., Dahlquist, E., Skoglund, R., & Jonasson, D. (2017). A driver advisory system with dynamic losses for passenger electric multiple units. Transportation Research Part C: Emerging Technologies, 85, 111-130.

VI Ghaviha, N., Bohlin, M., Holmberg, C., Dahlquist, & E. Speed Profile Optimization of Catenary-free Electric Trains with Lithium-ion Batteries (Manuscript under review)

Part of this thesis (Papers I and II) was previously included in the licentiate thesis "Energy Optimal Operation of Electric Vehicles: Development of a driver advisory system" (Ghaviha, 2016).

The following publications by the author are not included in this thesis.

- Ghaviha, N., Wallin, F., Dahlquist, E., & Bohlin, M. (2014, December). An Algorithm for Optimal Control of An Electrical Multiple Unit. In Proceedings of the 55th Conference on Simulation and Modelling (SIMS 55), Modelling, Simulation and Optimization, 21-22 October 2014, Aalborg, Denmark (No. 108, pp. 300-307). Linköping University Electronic Press.

- Ghaviha, N., Bohlin, M., Wallin, F., & Dahlquist, E. (2015). Optimal control of an emu using dynamic programming. Energy Procedia, 75, 1913-1919.

- Campillo, J., Ghaviha, N., Zimmerman, N., & Dahlquist, E. (2015, March). Flow batteries use potential in heavy vehicles. In Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles (ESARS), 2015 International Conference on (pp. 1-6). IEEE.

- Shashaj, A., Bohlin, M., & Ghaviha, N. (2016, June). Joint optimization of multiple train speed profiles. In Compatibility, Power Electronics and Power Engineering (CPE-POWERENG), 2016 10th International Conference on (pp. 478-483). IEEE.

- Campillo, J., Dahlquist, E., Danilov, D. L., Ghaviha, N., Notten, P. H., & Zimmerman, N. (2017). Battery Technologies for Transportation Applications. In Technologies and Applications for Smart Charging of Electric and Plug-in Hybrid Vehicles (pp. 151-206). Springer, Cham.

- Ghaviha, N., Energy Optimal Operation of Battery Driven Trains. ORbit medlemsblad for Dansk Selskab for Operationsanalyse og Svenska Operationsanalysföreningen, (2016)

Contents

List of Figures

List of Tables

Nomenclature

Abbreviations

ATO	Automatic Train Operation
C-DAS	Connected Driver Advisory System
CATO	Computer Aided Train Operation
DAS	Driver Advisory System
DC	Direct Current
DP	Dynamic Programing
EETC	Energy Efficient Train Control
EMU	Electrtic Multiple Unit
IPEMU	Independet Powered Electric Multiple Unit
LRV	Light Rail Vehicle
MCM	Motor Converter Module
OESS	On-board Energy Storage Systems
RAM	Random Access Memory
SESS	Stationary Energy Storage Systems

Symbols

η	Efficiency of the propsulsion system	$[\%]$
$\eta_{Converter-Modules}$	Efficiency of the converter module	$[\%]$
$\eta_{Gearbox}$	Efficiency of the gearbox	$[\%]$
η_{Motor}	Efficiency of the motor	$[\%]$
$\hat{y}_i$	Modeled values	$[-]$
ω	Motor speed	[rpm]
π	Series of control variables	$[-]$

π^*	Optimum series of control variables	$[-]$
τ	Motor torque	$[\mathrm{N\,m}]$
A	Coefficient for the generic battery model	$[\mathrm{V}]$
A_{rr}	Coefficient of Davis Formula	$[\mathrm{kN}]$
B	Coefficient for the generic battery model	$[\mathrm{A^{-1}\,h}]$
B_{rr}	Coefficient of Davis Formula	$[\frac{\mathrm{N}}{\mathrm{km/h}}]$
C_{rr}	Coefficient of Davis Formula	$[\frac{\mathrm{N}}{\mathrm{km/h^2}}]$
E_0	Battery open circuit voltage	$[\mathrm{V}]$
E_{Ah}	Charge consumption on battery	$[\mathrm{A\,h}]$
E_{kWh}	Energy consumption on DC Link	$[\mathrm{kW\,h}]$
E_{max}	Maximum energy capacity of the battery	$[\mathrm{kW\,h}]$
F_g	Gradient Force	$[\mathrm{kN}]$
F_t	Tractive Force	$[\mathrm{kN}]$
F_{rr}	Running Resistance	$[\mathrm{kN}]$
f_{sw}	Switching frequency	$[\mathrm{Hz}]$
$g(x,u)$	Transition cost	$[-]$
h	Change in elevation of the track	$[\mathrm{m}]$
$I \cdot T$	Charge consumed from the battery	$[\mathrm{A\,h}]$
I_{bat}	Current on the battery	$[\mathrm{V}]$
$J^*(x)$	Minimum cost-to-go	$[-]$
$J_\pi(x)$	Cost-to-go	$[-]$
K	Coefficient for the generic battery model	$[\frac{\mathrm{V}}{\mathrm{Ah}}]$
k	Coefficient of the regression model	$[-]$
$Loss_{MCM}$	Power loss in MCM	$[\mathrm{kW}]$
m	Train Mass	$[\frac{\mathrm{m}}{\mathrm{s}}]$
n	Sample size	$[-]$
P	Power	$[\mathrm{kW}]$

p	Coefficient of the regression model	$[-]$
P_{aux}	Power consumption of the auxiliary systems	[kW]
P_{loss}	Power loss	[kW]
Q	Maximum charge capacity of the battery	[A h]
q	Coefficient of the regression model	$[-]$
R	Internal resistance of the battery	[Ω]
r	Receptivity of the power grid	$[-]$
$RMSE$	Room mean square error	$[-]$
s	Distance traveled	[m]
SoC	State of charge	$[-]$
T	Last time step in the horizon	$[-]$
t	Time	[h]
u	Control variable	$[-]$
v	Velocity	$[\mathrm{m\,s^{-1}}]$
V_{bat}	Voltage on the battery	[V]
V_{grid}	Line voltage of the grid	[V]
V_{sim}	Line voltage of during the simulation	[V]
x	State of the system	$[-]$
y_i	Reference values	$[-]$

Part I:

Thesis

1. Introduction

In total, the transportation sector is responsible for 24.7% of the CO_2 emissions and 28.8% of energy consumption on the global scale (IEA & UIC, 2017). The railway sector accounts for 4.2% and 1.9% of the share of the whole transport sector in CO_2 emissions and energy consumption, respectively (IEA & UIC, 2016). One reason for this low share is the high capacity of railway systems and their high efficiency, which lead to lower emission and energy consumption per passenger and tonne. On the other hand, the share of railway in terms of total trips globally is only 6.9%. The share of passenger trips is even lower, coming after road and aviation with 6.7% (IEA & UIC, 2017). Since the Paris Agreement in 2015, the International Union of Railways has set new goals to increase the share of the railway sector in transportation, while lowering CO_2 emissions (75% reduction) and energy consumption (60% reduction) by 2050 (IEA & UIC, 2016).

Reducing emissions and energy consumption involves different fields of research, two of which are the focus of this thesis: energy-efficient train units and energy-efficient train control (EETC) (Scheepmaker, Goverde, & Kroon, 2017).

EETC addresses the problem of controlling a train in order to minimize the energy consumption while keeping to a timetable. This is handled by the driver advisory system (DAS). DAS is a system that instructs a train driver on how to control a train in the most energy-efficient manner. In order to recommend an energy-efficient decision to drivers, the DAS needs to calculate an energy optimum speed profile for each trip. A comprehensive solution to the EETC problem and the resulting recommendation from a DAS should consider different types of constraints such as the followings: train configuration (i.e. braking system, tractive effort curve and power losses in the rolling stock), track profile (i.e. speed limits, curves and gradients), running resistance and the characteristics of the power and train network (i.e. power losses in the grid and the signaling system) (Miyatake & Ko, 2010). The optimum recommendation for a DAS system is the result of an optimization problem called energy-optimal train operation or speed profile optimization. This problem has been studied for many decades and different solutions are offered in the literature (e.g. see (Ichikawa, 1968) for one of the first published studies in this field). Different commercialized driver advisory systems are also already on the market (Panou, Tzieropoulos, & Emery, 2013). However, as most of the products are commercialized, much of the mathematical background and the development process behind designing such systems is not available.

Together with the advancements in the field of energy-optimal train operation, new train unit designs and configurations are also contributing to a more energy-efficient railway system. According to the report by the International Union of Railways, the specific energy consumption and CO_2 emission of freight and passenger rail transport have been reduced by more than 50% since 1975 (IEA & UIC, 2017). This reflects improvements as a result of increasing the efficiency of train operation as well as the

increase in the efficiency of the rolling stock. One reason for these improvements is the increase in popularity of electric traction and catenary systems at the expense of the diesel traction system. Electric traction systems have a higher efficiency compared to diesel traction. Moreover, modern passenger trains that use the catenary system are often equipped with a regenerative braking system, which converts kinetic energy to electric energy during the braking mode and feeds it back to the power grid. However, although regenerative brakes are currently still not used efficiently due to the low receptivity of the low utilized lines ((Hoffrichter, Miller, Hillmansen, & Roberts, 2012)), the technology is still able to increase efficiency through the inclusion of energy storage devices in the traction system of electric and diesel-electric trains (Shibuya & Kondo, 2011) (note that the presented information is on the train level, a more comprehensive study would include the whole energy supply chain, from the source to the wheel, also known as the well-to-wheel analysis (Hoffrichter et al., 2012)). There is, however, a financial barrier to the use of electric traction and overhead lines. The installation cost for 1 km of electrified railway line can be on the order of a million Euros, and there are also yearly maintenance costs (Baumgartner, 2001). Hence, although in some countries, such as Sweden, Italy and Korea, around 80% of lines are electrified, the share of electrified lines globally is only around 30% (IEA & UIC, 2017). Catenary-free operated electric trains with on-board energy storage devices are another potential replacement for diesel electric trains; they provide the advantages of electric traction on non-electrified lines while minimizing emissions.

Catenary-free operated electric trains are currently mostly in the prototype phase. Catenary-free light rail vehicles (LRV), due to their low weight and short journey distances, are mostly equipped with supercapacitors as the energy storage device (Becker & Dammig, 2016). For electric multiple units (EMUs) with higher mass and longer travel distances, storage devices with higher energy and power capacity are needed. The current concepts presented for catenary-free EMUs consist of a limited number of EMUs equipped with lithium-ion batteries and hydrogen fuel cells (Campillo et al., 2017; Alstom, 2016). Since the technology of catenary-free operated EMUs is still in its early phase, not much research is being done in the field of speed profile optimization for such trains. The limited research in this field focuses on LRVs using supercapacitors as the energy storage device (Miyatake & Matsuda, 2008).

1.1 Objective

The EETC problem has been studied for several decades. Scheepmaker et. al present a review of different methods and solutions for energy-efficient timetabling and train control (Scheepmaker et al., 2017). Panou et. al. assess the different driver advisory systems on the market (Panou et al., 2013). On the basis of current developments in the field of energy-efficient train operation, the following issues have been identified as knowledge gaps for the problem of energy-efficient single train operation:

- Almost all the research presented in the literature for speed profile optimization or energy-optimal operation of EMUs uses a constant efficiency factor for calculation of power losses in the propulsion system. The only exception is the research presented by Franke et. al. (Franke, Terwiesch, & Meyer, 2000). Nevertheless, there are no studies on the effects of detailed loss calculations on the final results.

- Although many driver advisory systems are already on the market, there are no significant publications on the development of a driver advisory system, the validation of such a system and the challenges that accompany it.
- The subject of energy-optimal train operation is well-studied, but the problem of energy-efficient operation of catenary-free EMUs is a new topic in the literature as well as the industry. Most of the research in this field considers a supercapacitor as the energy storage device. Supercapacitors are, however, used mostly for catenary-free operated LRVs. The main energy storage device used for inter-city regional EMUs is lithium-ion batteries. A comprehensive energy-optimal driving regimen for EMUs should consider the characteristics of lithium-ion batteries and their effects on the optimum speed profile (Miyatake & Ko, 2010).
- Alongside the mathematical formulations and optimization techniques for energy-optimal catenary-free operation of EMUs, an experimental evaluation of the results is needed. This includes validation of the models and the potential energy savings that can be achieved using energy-optimal driving regimens.

It should be noted that the focus of this research is on the EETC problem for EMUs. Unlike locomotive-hauled trains, EMUs do not use locomotives, and have one or more traction systems in the same cars that carry the passengers or goods. The problem is different than that in freight and heavy haul trains, as the different train scale and configuration, together with the longer journeys lead to different constraints in the optimization problem. Moreover, the focus of this research is on single train operation. Consideration of the whole train network adds new dimensions to the optimization problem, such as losses in the grid and modeling of the receptivity of the line. Furthermore, the problem of energy-efficient timetabling is not in the scope of this work. Considering the knowledge gaps, the main contributions of this thesis are as follows:

1. Consideration of detailed power losses in the problem of energy-efficient train control
2. Development of a DAS for EMUs as an Android application
3. Offering a solution for the problem of energy-efficient control of catenary-free electric trains
4. Studying the effects of properties of the energy storage system on the results of speed profile optimization for catenary-free electric trains
5. Presenting potential energy saving achievable through energy optimal operation for catenary-free operated EMUs

1.2 Outline of the Thesis

The outline and structure of this thesis is as follows:

Chapter 2 *Related Work*

This chapter presents a summary of the current state of the art of the EETC problem for EMUs and catenary-free EMUs. The chapter includes three sections, each dedicated to the literature review of a topic: speed profile optimization of EMUs, driver advisory system and catenary-free operation of EMUs.

Chapter 3 *Research Framework*

This chapter presents the research framework of this thesis. It includes the presentation of the research questions and the methodology used to address each question.

Chapter 4 *Overview of the Papers*

A summary of the included papers is presented. The chapter also includes a presentation of how the papers relate to the research questions.

Chapter 5 *Mathematical Formulation*

Mathematical models and the theoretical background of the optimization approach are presented in this chapter. The chapter starts with the presentation of the train model and continues with the battery models used in the problem of speed profile optimization of battery driven trains. The chapter ends with a presentation of dynamic programing approach and its application for the problem of speed profile optimization and energy efficient train control.

Chapter 6 Results and Discussion

This chapter presents the major results of this research. The chapter is divided into two sections: results regarding the EETC for EMUs and results on the EETC for catenary-free operated EMUs. Chapter 6 ends with a discussion on the contribution of this thesis in the form of answers to the research questions.

Chapter 7 *Conclusion*

This chapter presents the overall conclusions of the thesis.

Chapter 8 Future Directions

The thesis ends with a short discussion on the possible future directions of the research in the field of energy-efficient train control.

The included articles are appended in the second part of the thesis.

2. Related Works

The problem of energy-optimal train operation has been studied for more than 60 years, and many mathematical solutions have been presented. A number of applied solutions and commercialized driver advisory systems have also been presented during the recent years. An overall literature review of the solutions is presented here, organized in three sections: speed profile optimization of EMUs, DAS and catenary-free operation of EMUs.

2.1 Speed Profile Optimization of Electric Multiple Units

The problems of optimal control and speed profile optimization of trains have been studied for many decades, with one of the first studies dating back to 1968 (Ichikawa, 1968). Two approaches have been used to solve the problem: coast control and optimal control. In terms of the operation scale, the problem can be addressed for a single train operation or multiple train operation on a network of trains. Furthermore, regarding train configuration, three categories of are considered for the problem with EMUs: EMUs operating under catenary, EMUs operated under catenary with a secondary energy storage device, and catenary-free operated EMUs.

In coast control the speed profile of the train is considered as one or multiple coasting phases during which the applied tractive effort from the traction motor is zero and the train moves under the influence of its kinetic energy. Figure 2.1 presents a speed profile including the coasting phases. The problem aims to find the optimum coasting gaps during operation to minimize the total energy consumption while keeping to the timetable.

Genetic and evolutionary based algorithms are the most common approaches presented in the literature for the coast control problem (see e.g. (Chang & Sim, 1997; Lechelle & Mouneimne, 2010; Erchao, Xin, & Yi, 2014; Bocharnikov, Tobias, & Roberts, 2010; Wong & Ho, 2004) for single train operation and (X. Yang, Chen, Li, Ning, & Tang, 2015) for multiple train operation). Acikbas et. al. (Acikbas & Soylemez, 2008) apply the genetic algorithm together with an artificial neural network to solve the coast control problem for a network of trains. The problem for single train operation has also been solved using an artificial neural network (Hui-Jen, Chao-Shun, Chia-Hung, Ching-Ho, & Chin-Yin, 2008). Other approaches such as heuristic search methods (Wong & Ho, 2004) and dual heuristic programming (Sheu & Lin, 2011; Jih-Wen & Wei-Song, 2012) have also been applied to the coast control problem.

The problem of speed profile optimization can also be viewed as an optimal control problem in which the optimum speed profile is determined regardless of coasting or cruising phases. Different solutions, such as ant colony optimization and fuzzy con-

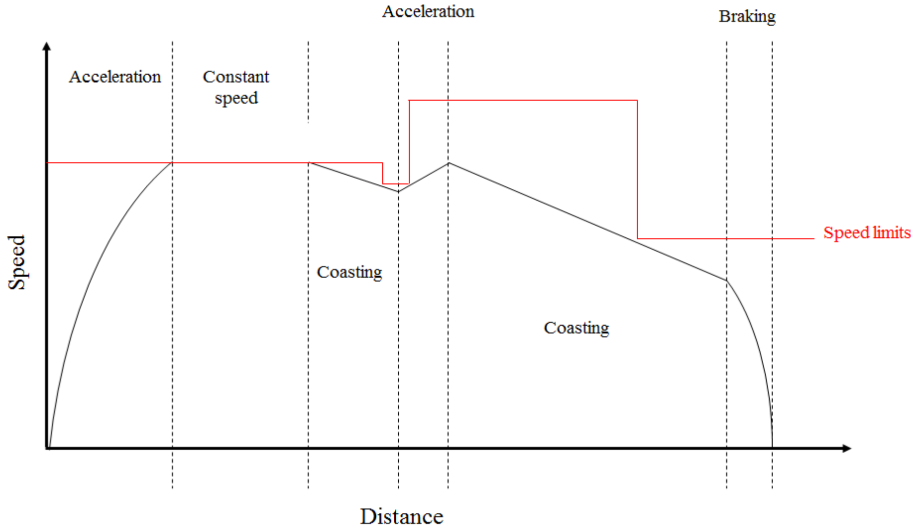

Figure 2.1: A speed profile including coasting phases

trol (Yasunobu, Miyamoto, & Ihara, 1983) and reinforcement learning (Yin, Chen, & Li, 2014), have been suggested for the optimum speed profile. Howlett (Howlett, 2000) presents a general formulation of the problem for trains with both continuous and discrete control and solves the problem using the Pontryagin maximum principle with the objective function of minimizing the fuel consumption for trains under continuous control and uses the Kuhn-Tucker equation for diesel-electric locomotives with notched control. Shuai et. al. (Shuai, Xiang, Tao, & Ziyou, 2013) also use the Pontroyagin maximum principle to optimize the timetable of subway trains based on energy-efficient operation. Liu and Golovitcher (Liu & Golovitcher, 2003) use the maximum principle for energy-optimal operation of rail vehicles. Both Liu and Golowitcher, and Shuai et. al. minimize the mechanical power consumption as the objective function. Miyatake and Ko formulate a problem for two train (Miyatake & Ko, 2007b) and multiple train (Miyatake & Ko, 2007a) operation with the objective function of minimizing the electrical power of the trains with a DC power feeding circuit, using the gradient method. Wang and Goverde study the speed profile optimization considering the multi train operations and operational constraints (Wang & Goverde, 2016, 2017a). Using the results of the speed profile optimization, Wang also studies the problem of energy efficient timetabling for multi-train operation (Pengling Wang, 2017).

Ko et. al. (Ko, Koseki, & Miyatake, 2004) present an algorithm based on Bellman's dynamic programming approach for speed profile optimization of EMUs with discrete control variable. The same principle (DP) is used to solve different variants of the speed profile optimization problem (e.g. multiple train operation (Tang, Wang, & Pe, 2014), variable efficiency (Franke et al., 2000) and fast DP with the consideration of passage points (Haahr, Pisinger, & Sabbaghian, 2017)).

Most of the research presented in this section assumes the same mass point train model with constant efficiency. Although there is theoretical research that assumes

variable efficiency (e.g. (Cheng & Howlett, 1993)), Liu and Golovitcher argue that including variable efficiency makes the problem and solutions too complicated for practical applications and that constant efficiency is sufficient (Liu & Golovitcher, 2003).

Franke et. al. (Franke et al., 2000) examined the variable loss by using a lookup table of pre-calculated loss values. Additionally, they reconfigured the standard formulation for the train energy-optimal control problem by using the kinetic energy per mass unit as one of the dimensions of the state variable, arguing that the new formulation reduces the nonlinearities of the problem.

Scheepmaker et. al. provide a review of different approaches used for the problem of energy efficient train control (Scheepmaker et al., 2017).

2.2 Driver Advisory Systems

In order to use the results of the speed profile optimization for minimizing energy consumption, a DAS needs to be developed based on the mathematical formulation. A DAS is a system that presents instructions to the driver regarding how to drive the train based on the solutions of the speed profile optimization or scheduling problem. Different DAS systems are already on the market with instructions based on off-line precalculated speed profiles or on-line optimization. Panou et. al. (Panou et al., 2013) provides a list of major DAS systems on the market and evaluates them on different aspects such as intelligence, user interface and communication.

There are two areas of research relating to designing a DAS: the mathematical solution and the implementation of the mathematical solution in the form of a DAS on the train. Most research in this field is focused on the mathematical formulation of the problem and the optimization approaches, and there is little published research on the implementation procedure or mathematical background of the currently available DAS systems. Exceptions are GreenSpeed by Cubris (Haahr et al., 2017), Energymiser by TTG Transportation Technology (A. R. Albrecht, Howlett, Pudney, & Vu, 2013) and ETO (Wang & Goverde, 2017b), for which the mathematical solution behind the DAS systems are available in the literature.

Regarding the design and interface, the procedure may vary for different mathematical solutions. Zhu et. al. (Zhu, Sun, Chen, Gao, & Dong, 2016) present design of a DAS based on a genetic algorithm approach. Wang and Goverde (Wang & Goverde, 2017a) present their approach of designing a DAS based on their mathematical solution. Yang et. al. (L. Yang, Liden, & Leander, 2013) discuss their experiences of deploying a CATO DAS, including the human/machine interaction.

According to Panou et. al. (Panou et al., 2013), a complete implementation of a driver advisory system should tackle three issues: drivers' needs, machine/human interaction and technology compliance. Drivers' needs presents the priorities for the drivers and their needs, machine/human interaction considers the facilitation of using the DAS and technology compliance focuses on the adaptability of the technology to the current standard technologies (e.g. signaling systems and ERTMS/ETCS[1]) (Panou et al., 2013). Moreover, to get the best efficiency out of a DAS, it should be connected to the train control centers and constantly updated by the train network timetable in-

[1]European Rail Traffic Management System/European Train Control System

formation. A DAS that is connected to the train control center is called a connected driver advisory system (C-DAS). A C-DAS should provide instructions for energy efficient train control considering the railway network traffic and timetable. As an example, CATO is the only C-DAS in Sweden and one of the first ones developed in the world. There are already projects going on in Europe to provide standard protocols for DAS and C-DAS (e.g. SFERA Project).

2.3 Catenary-free Operation of Electric Multiple Units

Catenary-free operated EMUs are EMUs that can run without overhead lines. These are mostly hybrid EMUs that work both under catenary and without catenary, using an energy storage system. The energy storage system can either be supercapacitor, battery or fuel-cell based. Supercapacitors are mostly used for catenary-free LRVs (Becker & Dammig, 2016), whereas among the few recent cases of long distance catenary-free medium sized EMUs, two use lithium ion batteries (Campillo et al., 2017; Kono, Shiraki, Yokoyama, & Furuta, 2014) and one is equipped with fuel cells (Alstom, 2016). There has also been an experiment with a prototype LRV that uses hydrogen fuel cells as the power source (Yoneyama, Yamamoto, Kondo, Furuya, & Ogawa, 2007). Batteries and fuel cells, compared to supercapacitors, have a disadvantage with respect to life cycle and cost. Thus, there have also been theoretical studies on hybrid energy storage solutions for EMUs (Tsukahara & Kondo, 2013).

Because of the immaturity of the technology, most of the research on speed profile optimization of catenary-free operated EMUs is focused on LRVs equipped with supercapacitors (see e.g. (Miyatake & Matsuda, 2008) for a solution based on DP and (Colak, Czarkowski, & de Leon, 2012) for a solution for the coast control problem). The solution presented in (Miyatake & Matsuda, 2008) and (Colak et al., 2012) cannot be applied to the problem of catenary-free operated EMUs with lithium-ion or fuel cells on board, as in both solutions, voltage of the supercapacitor is a determining factor and is used in the objective function and state variable. The only research in the field of EETC for catenary-free operated EMUs equipped with batteries is presented by Noda and Miyatake (Noda & Miyatake, 2016), who consider the characteristics of the battery using a fitted function from the battery discharge curve.

A well-formulated speed profile optimization solution for battery driven trains should consider the characteristics of the batteries. In general, three types of models used to monitor the performance of lithium-ion batteries have the potential to be used for train applications: mathematical, electro-chemical and electrical equivalent circuit network models. Electrochemical models are complex physics-based models that estimate the behavior of the battery based on electrochemical equations. Mathematical models model the battery using analytical methods and empirical formulas (Shafiei, Momeni, & Williamson, 2011). Electrical models simulate battery behavior by using electrical circuit components. Among the three categories, electrical circuit models avoid the complexities of high-fidelity electro-chemical models while providing sufficient accuracy for the problem of speed profile optimization (Fotouhi, Auger, Propp, Longo, & Wild, 2016). According to Fotouhi et. al., a comprehensive battery model should consider four characteristics of a battery: state of charge, temperature, rate of current and state of health (Fotouhi et al., 2016).

3. Research Framework

This chapter starts with the definition of the research questions. The chapter continues with the challenges for achieving the thesis objectives and answering the research questions. The approach used to tackle each research question is discussed in the last section of this chapter.

3.1 Research Questions

Based on the defined objectives and related works presented in the previous chapter, two main areas of research are considered for this thesis and two research questions are presented for each research area:

I Energy-optimal operation of EMUs
1. What is the procedure for designing a DAS from a theoretical solution?
2. How can we increase the accuracy of the power loss calculation for the problem of speed profile optimization and other similar applications?

II Energy-optimal operation of catenary-free operated EMUs
1. What are the main energy storage devices used for catenary-free operated EMUs, and what model is suitable for the speed profile optimization?
2. How can a dynamic programming approach be used for speed profile optimization of catenary-free operated EMUs considering the characteristics of the energy storage device, and what is the effectiveness of this approach?

3.2 Challenges

There are different challenges on the way of achieving the objectives of this thesis and to answer the research questions.

A DAS should be able to provide an optimal instruction during the operation and with the consideration of the fact that drivers might not follow the exact instruction. In other words, a DAS should be able to provide the optimum speed profile of any state during the operation in near real-time and the calculation time on the train should be minimum. Moreover, a newly developed DAS should be adaptable with the previous technologies and train configurations.

Speed profile optimization of electric trains are often done using the single mass point train model that models the mechanical power of the train. An efficiency factor is usually used in this model to consider the power losses of the propulsion system and train. However, detailed physical models based on electrical equations are needed to calculate accurate power loss values. For instance, losses in motor can be divided into different categories: iron loss, copper loss and mechanical loss (Zhang, Shi, Zhao,

& Wu, 2017). The same issue is also observed for the energy storage modeling. Detailed electrochemical models that provide a detailed estimation of the energy storage behavior are too complex for the applications that need fast simulation. Moreover, electrical models are also based on electrical equations. The main challenge in this regard is to incorporate a more accurate model of the power losses and behavior of energy storage device in the single mass point train model.

3.3 Methodology

To answer research questions $I.1$ and $I.2$, a DAS was designed based on development of the mathematical solution to the application on the train. For this purpose, an optimization approach and a train model were selected. Dynamic programming (DP) was used as the optimization technique, as it provides a global solution to the optimal control problem and has proved to be a reliable approach in theory (see e.g. (Franke et al., 2000) and (Haahr et al., 2017)). Moreover, the single mass point train model is used to model the train performance. This model, while being simple, provides an overall view of the mechanical power consumption, and has therefore been widely used for the problem of speed profile optimization. Panou et. al. notes that portable devices such as smartphones have the potential to be used for the interface of future driver advisory systems (Panou et al., 2013). The DAS was developed as an Android application for smartphones, because current smartphones are capable of providing enough information for the DAS. Furthermore, to answer research question $I.2$. and to improve the power loss calculations for the speed profile optimization and dynamic simulation, a regression model is used in place of constant efficiency. In order to test the reliability and speed of DP, the DAS was tested for a specific train and and line section. The case studied for this purpose was a Bombardier Regina EMU and the line section was a part of the Mälaren double track line in Sweden.

Research question $II.1$ is answered by a review on the application of energy storage devices in the railway sector. As a result of the review, batteries are recognized as one of the two main types of energy storage device used in catenary-free operation. Research question $II.1$ is further answered by incorporating the energy storage characteristics using a battery model in the popular mass point train model used in speed profile optimization. By including the battery model in the train model, state of charge of the energy storage device is estimated based on the mechanical power.

Electrical circuit models are identified as a suitable model to model the behavior of the battery for speed profile optimization. This type of model is less complex than other battery models, and provides acceptable accuracy. Moreover, electrical circuit battery models have previously been successfully applied to electric and hybrid electric road vehicles. Two battery models that were previously used and validated for electric vehicles and hybrid electric vehicles are studied for this purpose. To answer research question $II.2$, the same DP-based approach used for the design of the DAS is adapted for catenary-free operated EMUs. The effectiveness of the approach is presented in the form of the potential energy saving compared to experimental measurements from a battery driven EMU during catenary-free operation. The case studied for the catenary-free EMUs is the Bombardier IPEMU battery train. The IPEMU

train was a prototype battery-driven EMU designed by Bombardier Transportation and tested on a line section in the UK.

4. Overview of the Papers

This chapter presents an overview of each included paper together with a clarification of my contributions. The chapter ends with a presentation of the relation between each of the research questions and the papers.

- Paper I: *Optimal Control of an EMU using Dynamic Programming and Tractive Effort as the Control Variable* (Ghaviha, Bohlin, Wallin, & Dahlquist, 2015)
  Built upon the solution offered by Gkortzas for the train operation on a level track with no speed limits (Gkortzas, 2013), this paper offers a solution for the speed profile optimization of electric trains on a non-level track and considering the local speed limits. The approach presented in this paper considers the tractive effort as the control variable. The paper continues with a discussion on a comparison of this approach with using change in the velocity as the control variable and concludes with a suggestion on the suitable approach for each type of train.

- Paper II: *Speed Profile Optimization of an Electric Train with On-board Energy Storage and Continuous Tractive Effort* (Ghaviha, Bohlin, & Dahlquist, 2016)
  This paper presents the first solution for speed profile optimization of catenary-free operated EMUs for trains with continuous tractive effort control instead of the notch system. The objective function used in the approach presented in this paper was to minimize the power consumption from the energy storage device. The storage device was assumed to be connected directly to the DC link. The characteristics of the storage device were not considered in this paper. The solution was tested through simulation of a trip on a line section in the UK. Results of this paper show that dynamic programming with change in the velocity as the control variable can be used to design a DAS for catenary-free operated electric trains.
  This paper also includes a short study on the environmental effects of using a catenary-free operated EMU instead of a similar sized diesel EMU.

- Paper III: *Review of Application of Energy Storage Devices in Railway Transportation* (Ghaviha, Campillo, Bohlin, & Dahlquist, 2017)
  In this paper I studied the application of three types of energy storage device in railway systems: supercapacitors, flywheels and batteries. The main application of these energy storage devices in railways is to harvest energy from regenerative brakes for later use, and consequently, to increase the efficiency of the whole system. The paper also includes the more recent application of energy storage systems in railway: catenary-free operation of electric trains. Two categories of energy storage systems were recognized in this study: stationary energy storage systems and on-board energy storage systems. The paper also includes a brief discussion on two main challenges in the application of energy storage systems.

Results of this paper show that catenary-free LRVs are mostly equipped with supercapacitors, whereas among the three storage systems, batteries are the main energy storage systems used for catenary-free EMUs.

- Paper IV: *Modeling of Losses in the Motor Converter Module of Electric Multiple Units for Dynamic Simulation Purposes* (Ghaviha, Holmberg, Bohlin, & Dahlquist, 2017)
  Speed profile optimization and EETC is not the only field in which the detailed calculation of losses is a challenge. In this paper I studied the detailed calculation of losses in the motor converter module of EMUs for mechanical power simulation purposes. In the mechanical simulation, power is represented by tractive effort times velocity, considering the efficiency of the whole propulsion system from the wheels to the power source (overhead lines or the energy storage device). The mechanical simulation gives an overall view of the energy consumption during a driving cycle. This paper presents a regression model generated from a validated and detailed electrical model to calculate the power losses in the motor converter module. I further studied the model for three train configurations and twenty-seven experiments. The results show that the presented model can provide a better estimation of power losses than using constant efficiency.

- Paper V: *A driver advisory system with dynamic losses for passenger electric multiple units* (Ghaviha, Bohlin, et al., 2017)
  This paper studies the process of designing a DAS based on dynamic programming. The same approach presented in the previous papers is used as the optimization approach. A main challenge in the energy-efficient train control problem is to obtain a detailed calculation of losses while keeping the calculation time to a minimum (Scheepmaker et al., 2017). Hence, this paper focuses on two main challenges of designing a DAS using dynamic programming: offline calculation time and the accuracy of energy calculations. The calculation time is minimized using heuristic state reducing rules and the accuracy of energy calculations is increased by using a regression model instead of a constant efficiency factor. The paper continues with a description of the process of designing a DAS as an Android application for smartphones. The DAS was tested on a line section of the Mälaren line in Sweden (Kolbäck - Västerås). The results show a significant improvement in energy calculations compared to previous approaches as well as a significant potential in energy saving compared to the current train control regimen in operation on this line section.

- Paper VI: *Speed profile Optimization of Catenary-free Electric Trains with Lithium-ion Batteries*, Nima Ghaviha, Markus Bohlin, Christer Holmberg, Erik Dahlquist
  Much of the research done in the field of EETC for catenary-free operated electric trains considers a light rail vehicle with supercapacitors as the energy storage device. In this paper I study the energy-efficient control of EMUs with lithium-ion batteries as the energy storage device. Two battery models are studied for the speed profile optimization: a simplified battery model and a dynamic battery model. The

optimization technique is the same as the one presented in paper II, with a new objective function: minimizing the charge taken from the batteries. Both battery models are validated using the measured values from the test runs of a battery driven EMU prototype designed by Bombardier. The results show that the simplified battery model can provide enough accuracy for the purpose of speed profile optimization. I further present the potential energy saving achievable through dynamic programming and show the improvements achieved as a result of this problem formulation.

Each research question is addressed by one or more of the appended articles. Table 4 presents the research questions and the corresponding articles.

Table 4.1: *Research questions and the papers including the answers*

Research Question	Article
Research Question I.1	Paper I & V
Research Question I.2	Paper IV & V
Research Question II.1	Paper III & VI
Research Question II.2	Paper II & VI

Paper I presents a basic dynamic programming approach. The approach is further developed in Paper V and adjusted for designing a DAS considering the detailed power losses. The approach presented in Paper V for the consideration of power losses is used in Paper IV to study power losses in the motor converter module during mechanical power simulation. The dynamic programming approach in Paper I is also adjusted for catenary-free operation in Paper II. Paper III reviews the application of the energy storage devices for the catenary-free operation. Based on the results of Paper II and Paper III, Paper VI offers a solution for the speed profile optimization catenary-free operated EMUs considering the energy storage characteristics. Figure 4 shows the relation between articles and research questions.

The author was the main contributer in all the papers and did all the studies and simulations under the supervision and with the feedback from the supervisors. In Paper III, Javier Campillo contributed to the description of the three energy storage technologies and technical discussions. The electrical modeling and studies in Papers IV, V and VI where done with the help of the coauthor Christer Holmberg. Robert Skoglund and Daniel Jonasson, coauthors of Paper V, were the contributers to the development of the Android application.

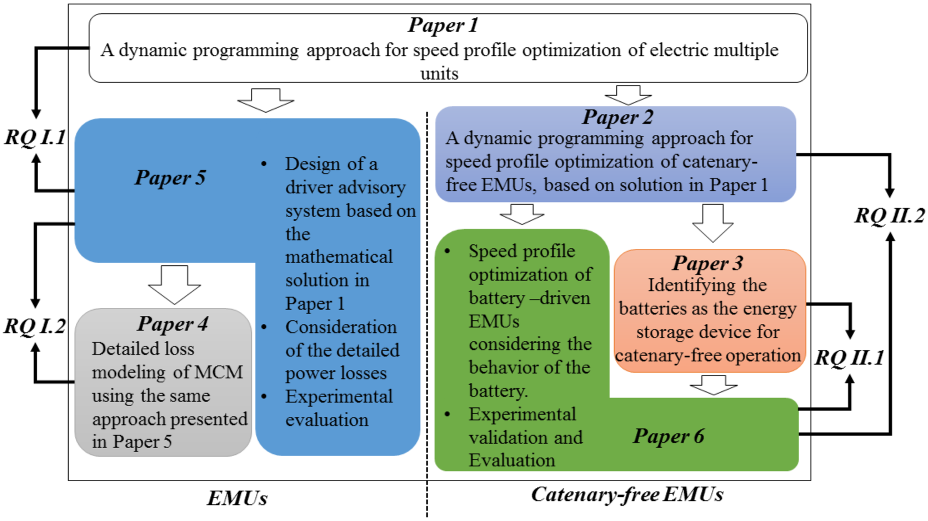

Figure 4.1: Relation between articles and research questions

5. Mathematical Formulation

This chapter includes an introduction to the models and the optimization technique used in this thesis.

5.1 Train Model

The focus of this research is on energy-optimal operation of EMUs, which are smaller in size than freight trains. This type of train can be represented by a single mass point model ((A. Albrecht, Howlett, Pudney, Vu, & Zhou, 2016)), which has been widely used for this purpose in the literature (see e.g. (Howlett, 2000)). This section describes the single mass point model used in this thesis.

We assume that the train has mass m and velocity v at time t; acceleration is $\frac{dv}{dt}$, the running resistance is F_{rr} and the gradient force applicable on the slope is F_g. Further, F_t is the tractive/braking force needed to move the train that is provided from the traction motor. Equation 5.1 shows the force balance of the train during operation:

$$m \cdot \frac{dv}{dt} = F_t - F_{rr} - F_g \tag{5.1}$$

The running resistance is calculated using the Davis formula, which is widely used to calculate the rolling resistance and aerodynamic resistance (A. Albrecht et al., 2016). Equation 5.2 presents the Davis formula:

$$F_{rr} = A_{rr} + B_{rr} \cdot v + C_{rr} \cdot v^2, \tag{5.2}$$

where A_{rr}, B_{rr} and C_{rr} are constants based on the train configuration. Coefficients may be determined experimentally or based on physical models, and are dependent on the track geometry and train specifications. The gradient force is calculated using equation 5.3:

$$F_g = m \cdot \frac{h}{1000}, \tag{5.3}$$

where h is the change in elevation for every 1000 m travelled, and $\frac{h}{1000}$ is therefore the estimated sine of the track slope. There is a limitation on the maximum tractive force available from the traction motor. Figure 5.1 shows the maximum available tractive force at different velocities, also known as the tractive effort curve.

The tractive effort curve is designed based on the acceleration and deceleration rate on a level track with no speed limits and is limited by the maximum torque available from the traction motor, the maximum power from the propulsion system and the pull-

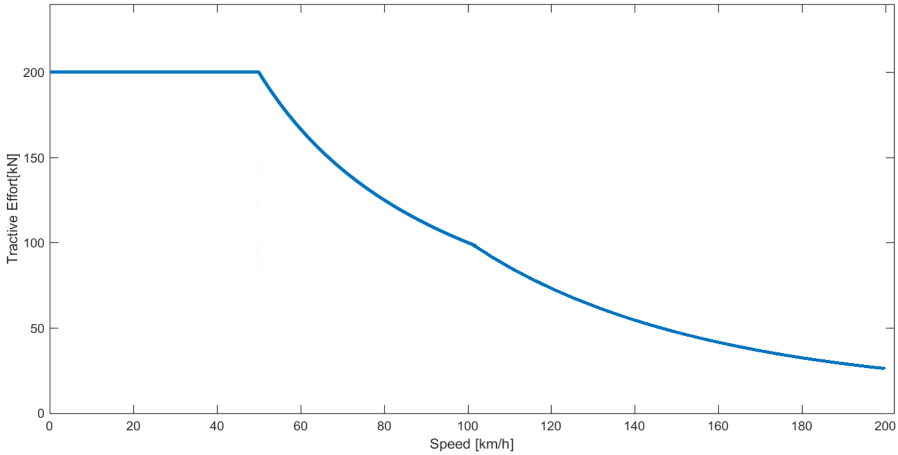

Figure 5.1: A generic tractive effort curve or the maximum tractive effort available in different velocities of an EMU (Paper V)

out torque of the induction motor (Paper V). The tractive effort curve is not designed for a specific line voltage and can be used within a range of line voltages.

The power consumption of the EMU is calculated using equation 5.4:

$$P = r \cdot (F_t \cdot v + P_{loss}) + P_{aux}, \tag{5.4}$$

where P is the total power consumption and P_{aux} is the power consumption of the auxiliary system, which is assumed to be constant. The train is equipped with regenerative brake systems and it is assumed that when the train is in braking mode, the kinetic energy is converted to electrical energy and transmitted back to the power grid. Receptivity of the line during regenerative braking is represented by r and is assumed to be constant. r is equal to 1 during acceleration. In the case of the battery driven EMU, the power consumption P is calculated as the power of the battery:

$$V_{bat} \cdot I_{bat} = F_t \cdot v + P_{aux} + P_{loss}, \tag{5.5}$$

where V_{bat} and I_{bat} are the voltage and current from the battery. P_{loss} represents the losses in the propulsion system, comprised of three main losses: gearbox loss, motor loss and converter loss. P_{loss} is usually calculated using a constant efficiency factor. Hence, equation 5.4 is rewritten as equation 5.6:

$$P = \begin{cases} \frac{1}{\eta} \cdot (F_t \cdot v) + P_{Aux} & \text{if } F_t > 0 \\ \eta \cdot r \cdot (F_t \cdot v) + P_{Aux} & \text{otherwise,} \end{cases} \tag{5.6}$$

where η is the efficiency of the whole propulsion system, which is the product of the efficiency of different components, as presented in equation 5.7:

$$\eta = \eta_{Gearbox} \cdot \eta_{Motor} \cdot \eta_{Converter-Modules} \tag{5.7}$$

η is the efficiency of the whole propulsion system from the wheels to the power source, $\eta_{Gearbox}$ is the efficiency of the gearbox, η_{Motor} is the efficiency of the motor and $\eta_{Converter-Modules}$ represents the efficiency of the converter modules. Besides the three mentioned losses, there are other minor losses that are negligible compared to the other three. The efficiency of each component however, is not constant in practice and varies with the velocity and the applied tractive effort.

5.2 Battery Models

Among the different types of battery models, electrical models are most suitable for power and dynamic simulations and they have been used for different transportation applications (Mousavi G. & Nikdel, 2014). Although electrochemical models are the most accurate model type, they are based on detailed electrochemical and differential equations and are too complex for dynamic simulation purposes.

Two electrical circuit equivalent battery models were studied for this research: the simplified battery model and the generic battery model. Both these models can be used for different types of batteries (Fotouhi et al., 2016). The few design variables of both models can be estimated from the manufacturer's data sheets, making the models easy to use (Tremblay & Dessaint, 2009). As well as transportation applications, the two battery models have also been used for several other purposes, such as wind power generation (Puleston, Valenciaga, Battaiotto, & Mantz, 2000) and DC micro grid systems (Xu & Chen, 2011). Generic characteristics of these battery models that make them applicable for batteries with different chemistries and their ease of use makes them a suitable option for the speed profile optimization application.

The simplified battery model models the terminal voltage as a function of current, whereas the generic battery model models the terminal voltage based on both current and state of charge. State of charge in both models is calculated using equations 5.8 (also known as the Coulomb Counting method (Rivera-Barrera, Muñoz-Galeano, & Sarmiento-Maldonado, 2017)):

$$\frac{dSoC}{dt} = -\frac{I_{bat} \cdot dt}{Q} \tag{5.8}$$

where I_{bat} is the current, $\frac{dSoC}{dt}$ is the derivative of state of charge over time, t is the time in h, SoC is the state of charge and Q is the total battery capacity in A h.

5.2.1 Simplified battery model

In the simplified battery model, the battery is modeled as a voltage source and an internal resistance (Johnson, 2002). Thus, the battery voltage depends on the current.

$$V_{bat} = E_0 - I_{bat} \cdot R, \tag{5.9}$$

where E_0 is the battery constant voltage value and R is its internal resistance. Further, V_{bat} is the voltage of the battery.

5.2.2 Generic battery model

The generic battery model is a more detailed version of the simplified battery model which considers the current state of charge in the model:

$$V_{bat-dischr} = E_0 - R \cdot I_{bat} - K \cdot (\frac{Q}{Q - I \cdot t}) \cdot (I \cdot t + I^*) + A \cdot \exp(-B \cdot I \cdot t) \tag{5.10}$$

$$V_{bat-chr} = E_0 - R \cdot I_{bat} - K \cdot (\frac{Q}{I \cdot t - 0.1 \cdot Q}) \cdot I^* - \frac{Q}{Q - I \cdot t} \cdot I \cdot t + A \cdot \exp(-B \cdot I \cdot t), \tag{5.11}$$

where $V_{bat-dischr}$ and $V_{bat-chr}$ are the battery voltage during discharge and charge, respectively. Q is the battery capacity, I is the battery current and t is the time passed. $I \cdot t$ represents the integral of the total charge taken from the battery which is calculated based on the state of charge. Further, I^* is the filtered current, which can be assumed to be equal to the current (Tremblay & Dessaint, 2009). The constants A in V, B in $(\text{Ah})^{-1}$ and K in $\frac{\text{V}}{\text{Ah}}$ are taken from the discharge curve of the battery ((Tremblay, Dessaint, & Dekkiche, 2007; Tremblay & Dessaint, 2009)). Assume Figure 5.2 is the discharge curve of a lithium-ion battery.

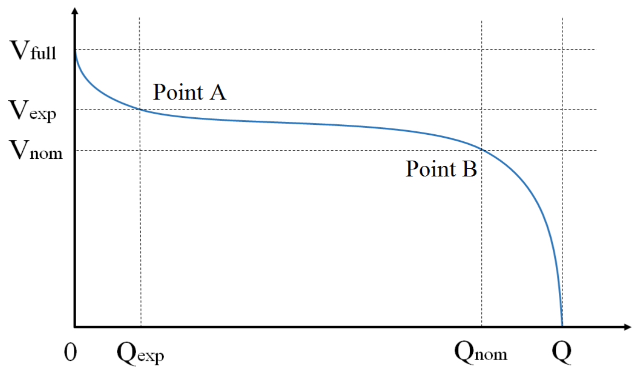

Figure 5.2: A typical discharge curve of a lithium-ion battery with the constant current load. The x axis shows the charge taken from the battery.

Coefficients of A, B and K are extracted using equations 5.12, 5.13 and 5.14 (Tremblay et al., 2007; Tremblay & Dessaint, 2009):

$$A = V_{full} - V_{exp} \tag{5.12}$$

$$B = \frac{3}{Q_{exp}} \tag{5.13}$$

$$K = \frac{(V_{full} - V_{nom} + A \exp(-B \cdot Q_{nom} - 1)) \cdot (Q - Q_{nom})}{Q_{nom}}, \tag{5.14}$$

where V_{exp} and Q_{exp} are the voltage and battery capacity at Point A, and V_{nom} and Q_{nom} are the voltage and capacity at Point B, depicted in Figure 5.2. Further, V_{full} represents the maximum voltage of the battery under load.

5.3 Dynamic Programming

Dynamic programming is selected as the optimization technique for this study. It is an effective optimization technique that has been previously used for the speed profile optimization and trajectory optimization (see e.g. (Franke et al., 2000) and (Haahr et al., 2017)). It has also been used for other application such as the trajectory optimization of heavy vehicles ((Hellström, Åslund, & Nielsen, 2010)) and aircrafts ((Menon & Park, 2016)). Moreover, application of DP will ensure the fast response time during the operation. Dynamic programming is a two stage process: backward iteration or optimization and forward iteration or simulation. Figures 5.3 and 5.4 present the two stages of dynamic programming.

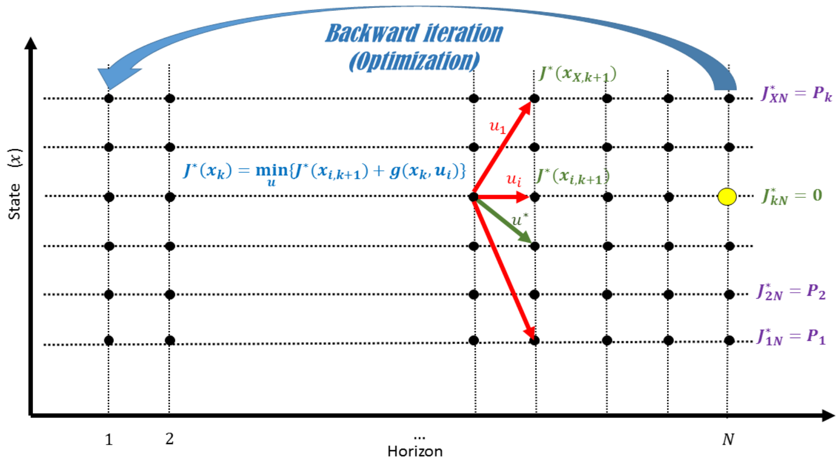

Figure 5.3: Backward iteration of dynamic programming approach

Three variables are needed for a dynamic programming solution: state variable (i.e. x), control variable (i.e. u) and independent variable, which represent the optimization horizon. Dynamics of the system is recognized using equation 5.15 and the three variables of state, control and horizon:

$$x_{i,k+1} = f(x_k, u_i), \tag{5.15}$$

meaning that the next state in the horizon after state x_k is determined according to the applied control variable (i.e. u_i). Transition cost $g(x_k, u_i)$ is defined as the cost when control variable u_i is applied to the state variable x_k. The aim is to get from the initial state x_0 to the final state x_N, following a series of control and state variables that minimize the total cost. If π is a series of control variables that can be applied to state x_k ($\pi = u_k, \ldots, u_{N-1}$), the total cost-to-go of applying π to state x_k is calculated

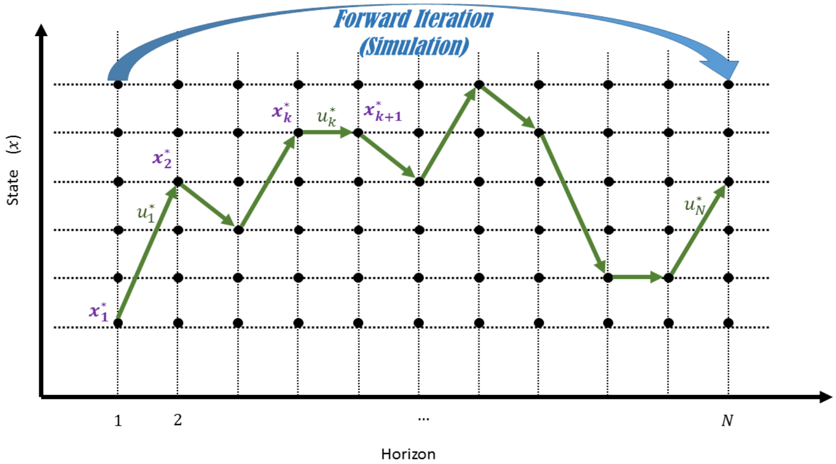

Figure 5.4: Forward simulation of dynamic programming approach

using equation 5.16:

$$J_\pi(x_k) = \sum_{i=k}^{N-1} g(x_i, u_i) + g_N(x_N), \tag{5.16}$$

where $J_\pi(x_k)$ is the total cost-to-go and $g_N(x_N)$ is the cost at the terminal state x_N. The problem is therefore to find the value of π^* that minimizes the total cost-to-go, which can be written as equation 5.17:

$$J^*(x_k) = \min_\pi \sum_{i=k}^{N-1} g(x_i, u_i) + g_N(x_N) \tag{5.17}$$

If $J^*(x_{k+1})$ is known for all the values of states in the step $k+1$ in the horizon, equation 5.17 can be rewritten as equation 5.18, :

$$J^*(x_k) = \min_{u_i}\{g(x_k, u_i) + J^*(x_{i,k+1})\}, \tag{5.18}$$

where $x_{i,k+1}$ is calculated using equation 5.15. Further, u^* is declared as the control variable that minimizes the right-hand side of equation 5.18. If $g_N(x_N)$ is known, the optimum control variable for all the states in the horizon can be found by backward iteration in the horizon and using equation 5.18 (Figure 5.3). Having the optimum decision at all the states, by forward simulation in the horizon from any state, the optimum series of states and control variables can be found (Figure 5.4)(Papers V and I).

In this dissertation, and for the problem of speed profile optimization of both normal EMUs and catenary-free EMUs, time t is assumed as the horizon and T represents the last step in the horizon. In case of the normal EMU, the state of the system

is defined using two discretized variables of distance (i.e. s_k) and velocity (i.e. v_k), presented in equation 5.19 (Paper V).

$$x_k = (s_k, v_k) \tag{5.19}$$

For the battery driven EMU, a third variable is added in the state variable (Equation 5.20):

$$x_k = (s_k, v_k, soc_k), \tag{5.20}$$

where soc_k presents the state of charge of the battery (Paper II).

There are two options for the control variable (i.e. u_i) depending on the type of train. EMUs are equipped with one of two systems for control of the tractive effort: discrete control (i.e. a notch system) or continuous control. In the notch system, the driver has the option of selecting only certain percentages of the effort from the traction motor, whereas in continuous control, the driver has access to all the values of tractive effort. For trains with the notch system, the notch number or the corresponding tractive effort is used as the control variable, whereas for trains with continuous control, change in the velocity is used as the control variable (Paper I). Energy consumption in kWh is set as the cost function. For the case of battery driven EMUs, energy consumption at the battery in Ah (i.e. charge taken from the battery) is also studied as the cost function.

6. Results and Discussion

This chapter presents the results of the research and discusses outcomes in the form of answers to the research questions. The chapter starts with a presentation of the results for the normal EMUs, followed by the results for the battery driven EMUs. The chapter continues with a discussion on the presented results and ends with the discussion on the contribution of the thesis in the form of the answers to the research questions.

For validation and evaluation purposes, data from two trains were used. For the case of EMUs, a Regina EMU was considered as the case study. This is a 2 car EMU manufactured by Bombardier, which is in service with several train companies including SJ. Regina can travel at speeds up to 200 $\mathrm{km\,h^{-1}}$ and seat 167 passengers. The test track used in this study was a double-track section of the Mälaren line in Sweden from Kolbäck to Västerås where the Regina EMU is in service. For the battery driven EMU, the data from the prototype battery driven EMU (IPEMU) developed by Bombardier was used. IPEMU was originally a reconfigured 4 car Bombardier Electrostar Class 379 EMU equipped with lithium-ion batteries. The train was tested between Harwich International and Manningtree stations in Essex, UK.

6.1 Energy Optimal Operation of Electric Multiple Units

This section presents the results and solutions for the problem of energy-optimal operation of normal EMUs. The section starts with a consideration of detailed power losses and continues with the results of implementation of dynamic programming in an Android DAS application.

6.1.1 Detailed Power Losses

The speed profile optimization and energy-efficient train control approach presented in this research can be viewed as a part of mechanical power simulation. In mechanical power simulation, the power is calculated as velocity times tractive effort. This is different from electrical power simulation, in which power is calculated as current times voltage. Mechanical power simulation gives an overall view of the whole energy consumption in the train, whereas electrical power simulation is used for detailed energy and loss calculations for each component.

Assume a tractive effort curve as presented in Figure 5.1. The tractive effort curve shows a maximum tractive effort available at each velocity. In other words, during a driving cycle (a trip from start to finish), a certain number of the points under the

tractive effort curve are used. Figure 6.1 shows the applicable points for a certain train configuration, and Figure 6.2 presents the applied tractive efforts during a driving cycle.

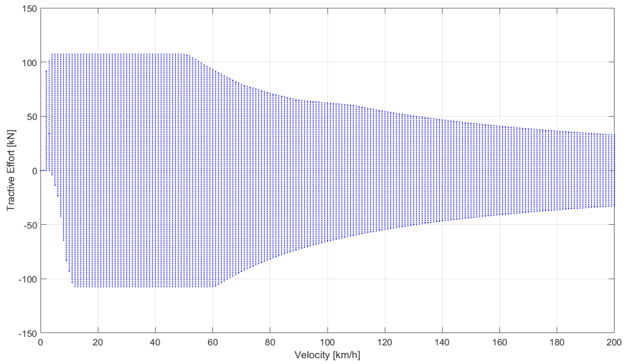

Figure 6.1: Applicable tractive efforts at each velocity for a certain train configuration

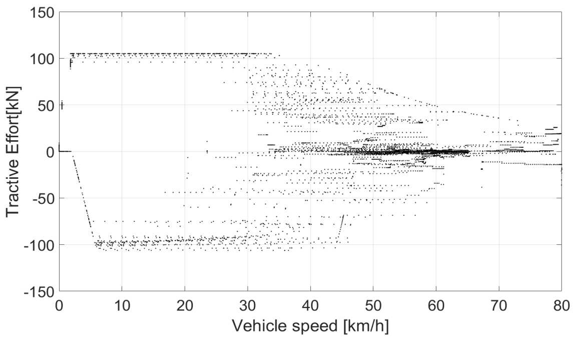

Figure 6.2: Example of the applied tractive effort points during a driving cycle (Paper IV)

A common approach to calculate the power losses during mechanical power simulation is to use a constant efficiency. The more accurate approach to calculate the power losses is to use detailed electrical equations and physical models. Figure 6.3 presents a comparison between the power loss calculation for all the points from Figure 6.1 using constant efficiency and detailed electrical models.

Detailed electrical losses in this thesis are calculated using an in-house validated energy calculation software developed by Bombardier Transportation. In order to benefit from the high accuracy of the electrical loss models in the speed profile optimization and mechanical power simulation, a fitted polynomial of the electrical losses presented in Figure 6.3 is generated. This regression model can then be used to calculate the power losses of different driving cycles (for instance the points presented in Figure 6.2).

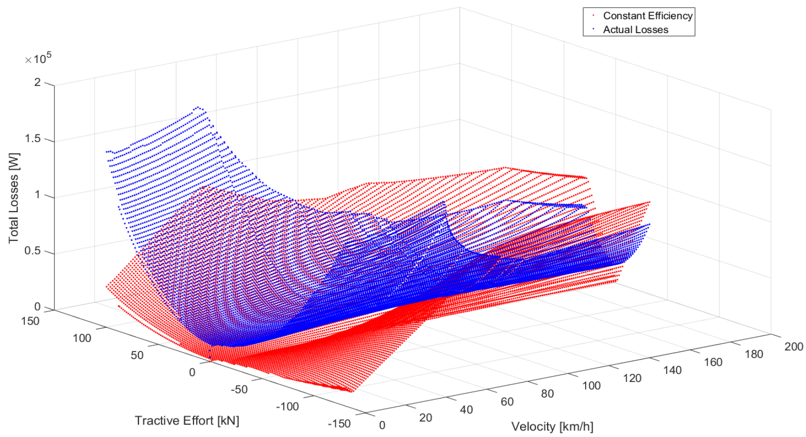

Figure 6.3: Comparison of the loss calculation using a constant efficiency factor and detailed electrical equations

For the application of speed profile optimization, the regression model is generated to calculate the total losses in the propulsion system and the train. Equation 6.1 presents the regression model generated for the power loss calculation of the Regina train. Because of the difference in line voltage during acceleration and braking, one model is generated for each phase.

$$P_{loss} = \begin{cases} \sum_{n=0}^{4}\sum_{m=0}^{2} p_{mn} \times v^n \times F_t^m & \text{if } F_t > 0, \\ \sum_{n=0}^{4}\sum_{m=0}^{2} q_{mn} \times v^n \times F_t^m & \text{otherwise,} \end{cases} \tag{6.1}$$

where p_{mn} and q_{mn} are the constants and P_{loss} represents the power losses in the whole propulsion system. The orders of the polynomials in equation 6.1 are chosen based on the study on the root mean square error of different polynomials with different orders (Paper V). Root mean square error is calculated using equation 6.2:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}, \tag{6.2}$$

where $RMSE$ is the root mean square error, y_i is the reference value, $\hat{y}_i$ is the modeled value and n is the sample size. Tables 6.1 and 6.2 present the root mean square error of the estimated power losses for different polynomials.

The correlation coefficient of the regression model with the results of the energy calculation software is 0.99, whereas the correlation coefficient of the loss points calculated by a constant efficiency factor with the electrical model is 0.55. Since the new regression model is based only on the tractive effort and velocity, it can be combined with the single mass point train model and used instead of the constant efficiency factor in speed profile optimization and energy-efficient train control.

Table 6.1: Root mean square error of different polynomials for acceleration section (Paper V)

V power to	F_t power to	RMSE[W]
1	1	6937
1	2	2857
1	3	2411
1	4	2338
2	1	6828
2	2	2646
2	3	1686
2	4	1496
3	1	6748
3	2	1449
3	3	1244
3	4	1119
4	1	6118
4	2	1377
4	3	1117
4	4	1116

Table 6.2: Root mean square error of different polynomials for braking section (Paper V)

V power to	F_t power to	RMSE[W]
1	1	7264
1	2	1498
1	3	1475
1	4	1462
2	1	7186
2	2	1491
2	3	1355
2	4	1305
3	1	7064
3	2	1058
3	3	1024
3	4	894.6
4	1	6688
4	2	852
4	3	764.6
4	4	752.2

The same approach can be used for the loss calculation of different components during mechanical power simulation for other applications. Losses in a propulsion system comprise of three main components: gearbox loss, motor loss and converter loss. In this thesis, loss calculation in the motor converter module (MCM) is studied as an example. A nonlinear regression model is used for the modeling of the losses in MCM. Figure 6.4 presents the power losses of MCM for all the points under the tractive effort curve of an electric train configuration.

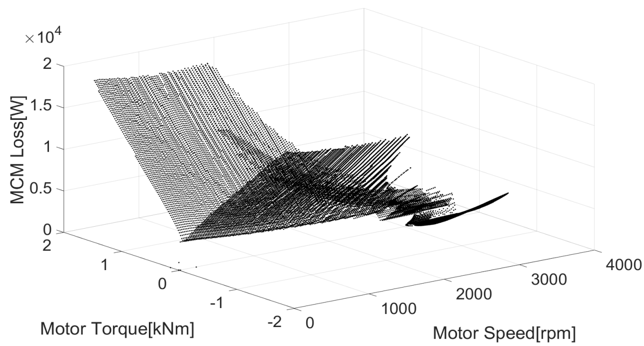

Figure 6.4: MCM power loss for all the points under the tractive effort curve of a certain electric train configuration (Paper IV)

The disturbances shown in Figure 6.4 above the motor speed of 2000 rpm are due to the change in the switching frequency of the converter. For the case of motor converter

module, the regression model is based on motor torque, motor speed and switching frequency variables. Tractive effort and vehicle speed can be used instead of motor torque and motor speed, respectively, as they directly correlate with these variables.

The regression model was generated for a certain line voltage. However, the line voltage is not always constant during operation, as it increases during braking mode, which causes a decrease in power loss compared to lower voltages. A solution for this issue is to generate a regression model for every line voltage. The other solution chosen for this case is to use linear scaling of the regression model based on the line voltage. Equation 6.3 presents the final regression model including linear scaling with the line voltage (Paper IV).

$$Loss_{MCM} = \frac{V_{sim}}{V_{grid}} \cdot \Big(\sum_{m=0}^{2}\sum_{n=0}^{1} \tau^m \cdot \omega^n + q_{mn} \cdot f_{sw} + p_{mn} \cdot f_{sw} \cdot \tau + k_{mn} \cdot f_{sw} \cdot \omega\Big), \tag{6.3}$$

where $Loss_{MCM}$ is the power loss in the motor converter module, f_{sw} is the switching frequency, τ is the motor torque, ω is the motor speed, and q_{mn}, p_{mn} and k_{mn} are constant coefficients. Further, V_{sim} is the line voltage during the simulation or operation and V_{grid} is the line voltage of the grid from which the regression model was generated.

Three regression models were generated for three types of electric train configurations and were used to calculate the total MCM energy loss for around eight driving cycles for each of the train configurations. MCM losses were also calculated for all the driving cycles using a constant efficiency factor. Results show that the total MCM losses calculated using the regression model differ by 2.3%, on average, from the losses calculated by the energy calculation software, whereas the losses calculated using a constant efficiency factor differ by 45.9% from the detailed losses calculated using the physical model.

The detailed electrical losses in this study were calculated using a validated energy calculation software. Other validated loss models can be used instead of the energy calculation software to generate the grids and regression models.

6.1.2 Driver Advisory System

This thesis studies the application of the presented dynamic programming approach for designing a DAS for EMUs. There are two types of systems for controlling the tractive effort in EMUs: the notch system and the continuous system. In the notch system, the driver has access to specific discrete percentages of tractive effort from the traction motor. In the continuous system however, the driver has continuous control over the tractive effort. Both systems are sometimes accompanied by a notch for cruising the train at a constant speed. The dynamic programming approach presented in Paper I and section 5.3 can be applied for both types of trains. However, it is preferable to use tractive effort as the control variable for trains with the notch system, whereas for trains with continuous tractive effort, change in velocity is the preferred control variable (Paper I).

One of the main challenges in the problem of energy-efficient train control is the conflict between the calculation time and the accuracy of the loss model (Scheepmaker et al., 2017). However, dynamic programming is known to

have a disadvantage in relation to the calculation time. Simulation results show that the backward iteration of dynamic programming as presented in section 5.3 for a trip of around 20 km can take up to 37 min. This is considering a constant efficiency factor for the calculation of power losses in the propulsion system (Paper V).

Consider Figure 5.3, which presents the backward iteration of a dynamic programming approach. During the backward iteration, an optimum decision is found for all the possible states in all the steps in the horizon. The state of the system is assumed to be the vector of distance and velocity, and time is assumed to be the horizon (see section 5.3). However, not all the states in all time steps are feasible for the train. Some states are outside the physical boundaries of the system. For instance, given that the train has a maximum acceleration rate, it cannot always reach a particular velocity at a particular time or distance. Considering the unfeasible states based on the system constraints, three heuristic state reducing rules are designed to reduce the amount of calculation during backward iteration (see Paper V for more details). Using the suggested state reducing rules, the calculation time was reduced to 20 min from 37 min.

The modified dynamic programming approach considering the state reducing rules and the new train model with detailed losses was used to design a DAS as an Android application for smartphones. The backward iteration is done off-line on an interface designed in MATLAB (i.e. off-line unit). The results of the backward iteration are saved as a binary file and used on-board the train on an Android application (on-line unit). Figures 6.5 and 6.6 present the procedure on the off-line and on-line units, respectively.

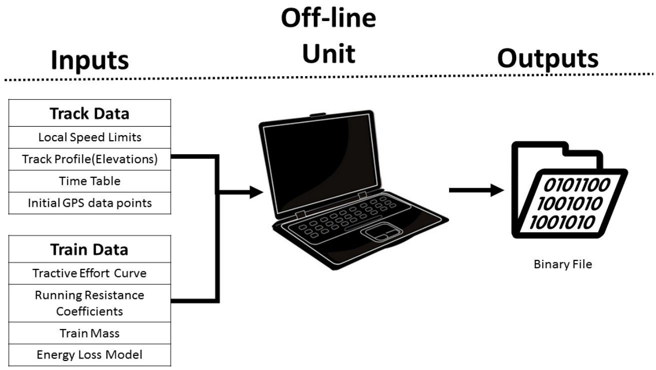

Figure 6.5: Off-line unit of the driver advisory system (Paper V)

The test runs of the application of the system on the line section from Kolbäck to Västerås indicate a potential of around 28% reduction in energy consumption.

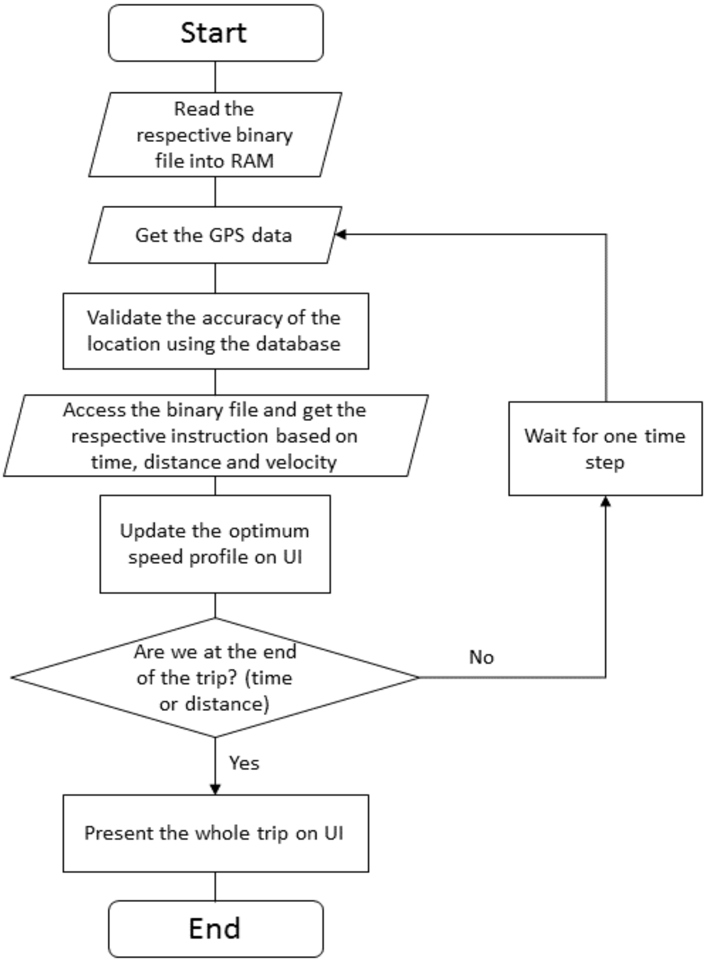

Figure 6.6: On-line unit of the driver advisory system (Paper V)

6.2 Energy Optimal Operation of Battery Driven Electric Multiple Units

The consideration of energy storage systems in the problem of speed profile optimization, leads to new problems by adding new constraints and dimensions to the original problem.

The main application of energy storage devices in railway is to harvest the energy from regenerative brake systems. Energy storage devices are used in two main categories: stationary energy storage systems (SESS) and on-board energy storage systems (OESS). SESS are storage systems that are installed on the track or in substations, whereas OESS are storage systems that are mounted on the train. There are three main storage devices that are currently in use in the railway transportation to

harvest the regenerative energy: batteries, supercapacitors and flywheels. The more recent application of energy storage devices in railway is for the catenary-free operation of electric trains. Lithium-ion batteries are the main energy storage device used for the application of catenary-free EMUs (Paper III).

The problem of energy optimal operation of an EMU with an on-board battery during catenary-free operation is solved in the second part of this thesis.

6.2.1 Battery Model

The battery models presented in section 5.2 can estimate the voltage of the battery under different loads and states of charge. Two validations are carried out to study the performance of the battery models for the purpose of speed profile optimization using the approach presented in this research.

In the first validation, the battery models are validated regarding the voltage estimation (equations 5.9, 5.10 and 5.11). The validation is done using actual measurements from test runs of a battery driven EMU. The results show that for the case of the IPEMU train, the generic battery model can provide slightly higher accuracy in terms of voltage estimation. The generic battery model can estimate the voltage with an average error of 0.63%, whereas the simplified battery model results in an average error of 0.77%.

In the dynamic programming approach used in this study (see 5.3), state of charge of the battery is a state variable (equation 5.20). Therefore, it is important to use a battery model that gives an accurate estimate of SoC. The other two state variables are distance and velocity. Moreover, the single mass point train model calculates the energy consumption using the mechanical power calculation (i.e. velocity times tractive effort). Therefore, the battery model, together with the train model, should be able to estimate SoC of the battery using the mechanical power calculation.

As presented in section 5.3, dynamics of the system is presented as a function of the current state variable and the applied decision variable (equation 5.15). Therefore, given that $x_k = (s_k, v_k, soc_k)$, equation 5.15 is rewritten as equation 6.4:

$$(s_{k+1}, v_{k+1}, soc_{k+1}) = f(s_k, v_k, soc_k, u_i) \tag{6.4}$$

For the case of the battery driven EMU, the control variable is applied tractive effort or notch number and the values of s_{k+1} and v_{k+1} are calculated using the kinetic equations (as presented in Paper I).

Let voltage on the battery be a function of the state of charge and the applied current:

$$V_{bat} = f(soc, I_{bat}), \tag{6.5}$$

where $f(soc, I_{bat})$ is dependent on the battery model: equation 5.9 for the simplified battery model, and equations 5.10 and 5.11 for the generic battery model. On the other hand, power on the battery is calculated using the kinetic equations (Paper II). Power on the battery is also equal to voltage times current, as presented in the left-hand side of equation 5.5. As the value of voltage times current is known from the equation 5.5, using equations 5.5 and 6.5, the values of I_{bat} and consequently soc can be calculated. Thus, a second validation is performed regarding the estimation of the state of charge

based on a battery model and a speed profile. We validate both battery models using a speed profile from a test run of a battery driven EMU. Figure 6.7 shows the speed profile of the test run, and Figure 6.8 presents a comparison between the measured state of charge on the train and the estimated values using both generic and simple battery models.

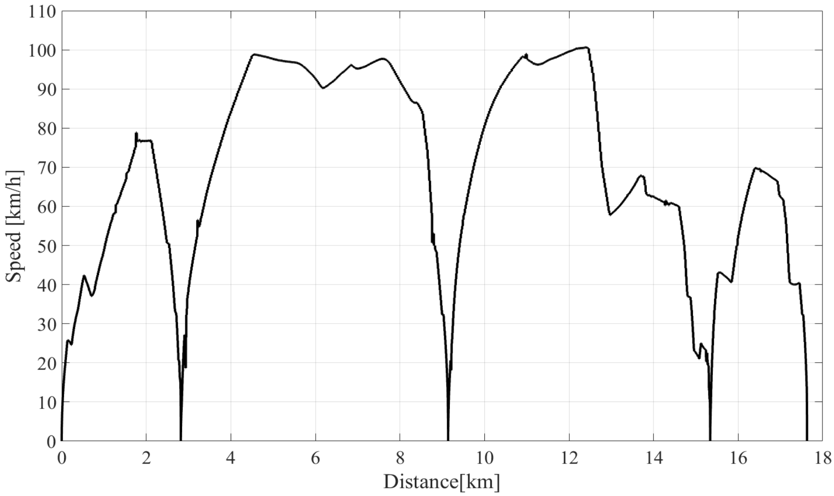

Figure 6.7: Speed profile of an experiment used for the validation of SoC estimation based on mechanical power (Paper VI)

The results of the validation show that both battery models can estimate the state of charge with similarly high accuracy.

6.2.2 Speed Profile Optimization

Speed profile optimization of the catenary-free operated battery EMUs is different than that of a normal EMU. Having a battery as the only energy source adds new constraints to the optimization problem. The main constraint is regarding the limited energy capacity of the battery. The first step for the consideration of the energy storage related constraints is to introduce the state of charge as the new state variable. Having state of charge as a state variable facilitates handling of any constraints related to the state of charge.

The objective function in the case of the battery driven EMU is minimizing the energy consumption from the battery. The energy consumption however, can be stated either in the form of the energy consumption on the DC link and in kWh or in the form of the charge consumption from the battery in Ah. Equation 6.6 shows the relation between the energy consumption on the DC link and charge consumption from the battery.

$$E_{kWh} = \frac{V_{bat} \cdot E_{Ah}}{1000}, \tag{6.6}$$

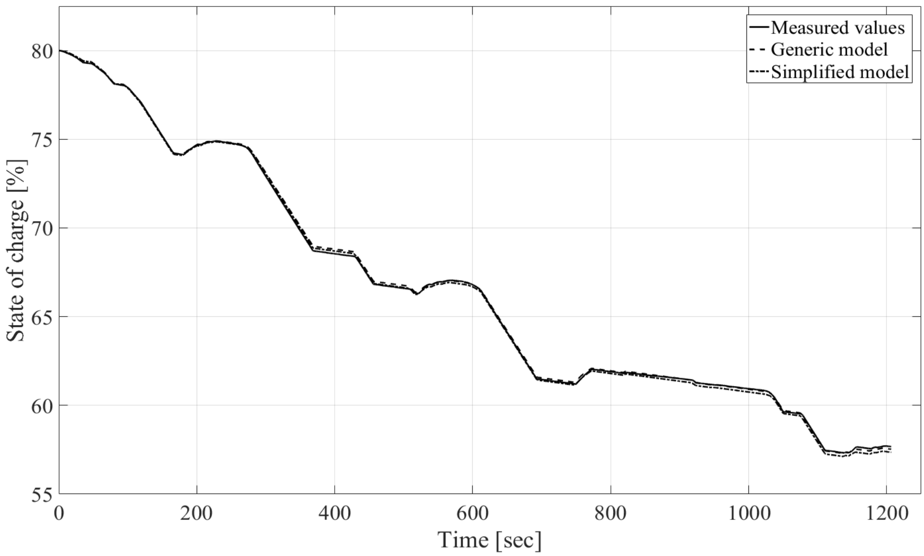

Figure 6.8: Measured state of charge compared with the modeled state of charge (Paper VI)

where E_{kWh} represents the energy consumption on the DC link and E_{Ah} presents the energy consumption in Ah from the battery. If the battery has a stable behavior in all conditions (i.e. V_{bat} is constant), minimizing E_{kWh} and E_{Ah} as the objective function will result in same speed profiles. In case of minimizing the energy consumption in kWh, the state of charge can also be determined in terms of kWh, as presented in equation 6.7 (Paper II).

$$\frac{dsoc}{dt} = -P \cdot dt / E_{max}, \tag{6.7}$$

where P is the power consumption in kW calculated using Equation 5.4 in section 5.1, dt presents time in h and E_{max} presents the maximum energy capacity of the battery in kWh. Equation 6.7 represents a simple energy balance model for modeling the energy storage device.

However, the voltage of the battery is not constant in all conditions and it is a function of different variables. Hence, to consider the characteristics of a battery, it is more suitable to minimize the charge in Ah as the objective function. In this thesis, the battery characteristics are included in the problem of speed profile optimization using the two previously mentioned battery models and the method presented in section 6.2.1.

The generic battery model provides accurate estimation of the battery voltage, but the optimization technique presented in this research is formulated such that only the battery charge consumption and state of charge are needed. Given that dynamic programming suffers from the curse of dimensionality, it is important to simplify the calculations for the backward iteration (Paper V). Therefore, given the complexity of the generic battery model and the similar accuracy of both models the simplified battery model was selected for the optimization.

A comparison between the test runs of the Bombardier IPEMU battery train and the respective optimum speed profiles generated by the dynamic programming approach using the simple battery model shows a potential 31.6% reduction in energy consumption. Figure 6.9 shows a comparison between the energy consumption of the actual driving cycles (circles) and the optimum energy consumption values generated as a result of the optimization (line).

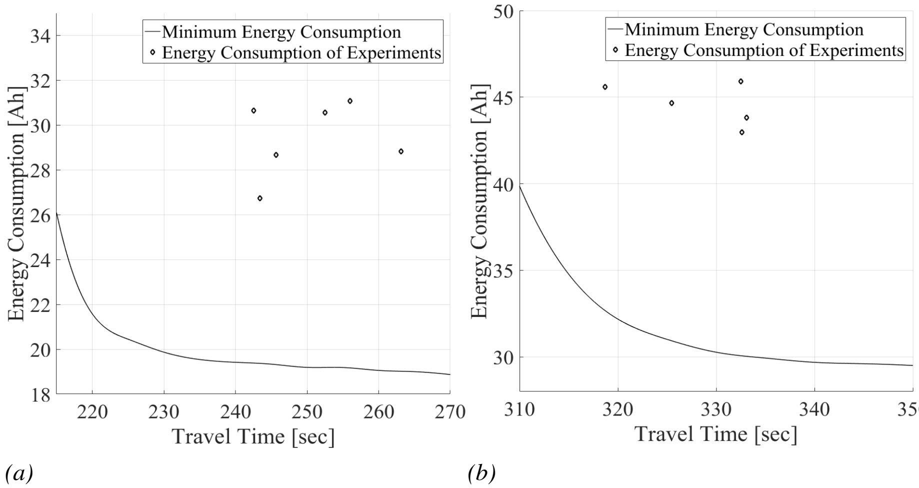

Figure 6.9: Comparison of the energy consumption between the experiments and the optimization approach for a trip of a)3 km and b)6.27 km (Paper VI)

6.3 Discussion

In this thesis, a regression model has been used to consider detailed power losses in the propulsion system. To study the effects of detailed losses on the optimization results, optimum speed profiles are generated for different trip sections between Kolbäck and Västerås using the two approaches. A comparison of the results shows that the speed profiles generated with the new loss model are 2.3% more energy-efficient than those generated using a constant efficiency factor (see Paper V). This can be a significant energy saving considering the fact that the power consumption of EMUs can be in the order of megawatts. Figure 6.10 shows a visual comparison of the speed profile generated using a constant efficiency factor and the speed profile generated using the regression model.

The regression model used in this research was based on physical models of different components in the propulsion system. Similar approaches, such as efficiency maps or look-up tables based on tractive force and velocity, can be used instead of a regression model to incorporate the detailed power losses in the problem of speed profile optimization.

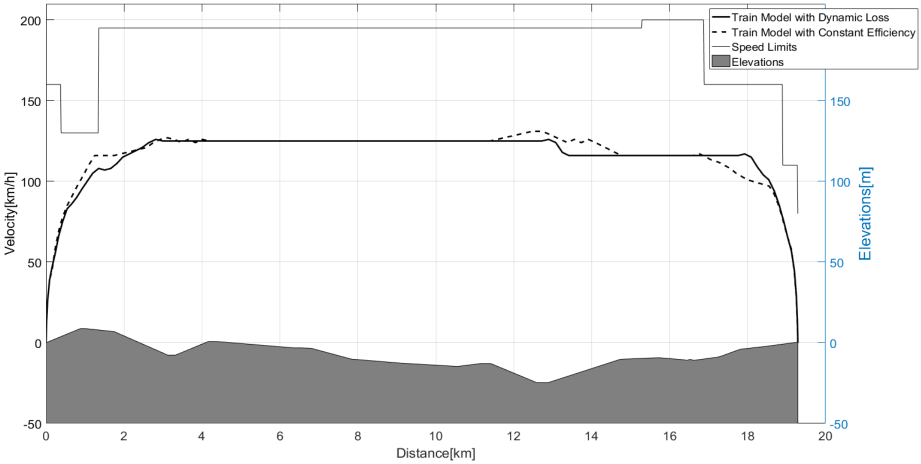

Figure 6.10: Comparison between the speed profiles generated using a constant efficiency factor and the regression model (Paper V)

In order to evaluate the performance of the optimization using the DAS for EMUs, different optimum speed profiles were generated using the optimization approach. As well as speed profiles for the whole trip, speed profiles were also generated for different points along the trip. These points were acquired from an actual driving cycle of a train. Thus, the DAS is shown to be responsive to mistakes the driver may make in following the recommendations of the system. However, because of time limitations in this research, the behavior of drivers toward the system was not studied. As an example, Figure 6.11 shows a screen shot of the Android DAS during operation. The red line shows the current state of the train on the track and the solid yellow line is the original optimum speed profile generated at the start of the trip. The solid blue line is the actual driving style of the driver and the dashed blue line represents the new optimum speed profile for the current state of the train. The dashed blue line is updated during the trip and considering the current state of the train.

As mentioned in section 5.3, dynamic programming is a two stage process: optimization and simulation. Optimization is done off-line and before the start of the trip, whereas simulation occurs on-board the train and during operation.

As all the results are saved off-line and uploaded into the Android application before the start of the trip, there is no need for communication between the off-line and on-line units during the train operation. Moreover, the experiments show that the application can look through the off-line results and provide the instructions during the operation in less than a second. In the Android application, the off-line solution is read into the random access memory (RAM) of the smartphone. A concern is that the RAM may not be sufficient for long trips, although no problem was observed for the case of the 20 km trip studied in this thesis. A potential solution to this problem is to split the off-line solution into smaller files and upload them in the RAM subsequently and during the operation.

The second set of results presented in this thesis address optimal operation of battery driven trains using a battery model. The two studied battery models were vali-

Figure 6.11: Screen shot of the Android DAS during the operation; box 1 shows the current speed and box 2 shows the recommended optimum tractive effort (Paper V)

dated against long driving cycles in which different operation phases were observed. However, the driving cycles did not include the whole range from 0 to 100% of the battery capacity. Nevertheless, the validation is still applicable, since the state of charge during the driving cycles were in the operating range recommended by most of the battery suppliers.

In this research, in contrast to using power consumption as the objective function as in the previous research, minimization of charge is assumed as the objective. Because of the voltage fluctuations of the batteries, charge in A h is a better indicator of the battery capacity. To study the effects of changing the objective function, both approaches were used to generate optimum speed profiles. Results of the comparison between the optimum speed profiles generated using charge in A h and power in kW h as the objective function show the improvement in energy efficiency. In the case of IPEMU, there is an improvement of around 0.23% in minimizing the charge consumption. However, it shown that in the case of energy storage devices with a less stable terminal voltage, the improvement in energy efficiency would be higher (Paper VI).

Formulation of the state variable in this thesis (equations 5.19 and 5.20), facilitates handling of the constraints on distance, velocity and state of charge. In dynamic programming, constraints are handled using a cost penalty. Different constraints are handled using this method in this thesis such as: local speed limits, maximum and minimum charge capacity, and the constraint regarding maximum tractive effort available in each velocity. It is expected that constraints on time (i.e. horizon) could also be treated with the same approach, although it has not been studied in this thesis.

These type of constraints include the constraint on the time passage points (Haahr et al., 2017).

The optimization solution presented in this thesis discretizes the variables to approximates the continuous state space. Discretization of variables results in an approximation of the cost-to-go values instead of the actual values of cost-to-go (see section 5.3). The accuracy of the approximation is dependent on the grid intervals, which means that the optimal cost-to-go may not be the global optima. The suitable grid intervals in this research are selected based on a compromise in the following criteria: calculation time of the backward iteration, time interval for the instruction to the driver, terminal error on state variables and value of energy consumption. The energy consumption and terminal error on state variables were assessed using the Bombardier in-house code. It is to be noted that although the assessment of the accuracy and sensitivity of the solutions to the grid size was out of the scope of this work, the final potential energy consumption reduction is credible as it was measured using a validated in-house tool. It is also because of the discretization errors that it is preferable to use notch number as the control variable for the trains with the notch system.

The dynamic programming approach used in this thesis was a basic dynamic programming approach; other approximate DP approaches (e.g. the dynamic programming approaches presented in (Haahr et al., 2017) and (Franke et al., 2000)) can also be used instead of the basic DP presented in this research to design a DAS considering the detailed power losses and characteristics of the battery.

6.4 Contribution to Knowledge

Based on the presented results and discussion, the contribution of this thesis is formulated as the answers to the research questions:

I Energy optimal operation of electric multiple units

1. *What is the procedure of designing a driver advisory system from a theoretical solution?* (Papers I and V)
   There is substantial research in the field of energy-optimal train operation, but not much is known regarding the application of mathematical solutions for the practical problem of energy-optimal train operation. Therefore, to answer this research question, the whole procedure of designing a DAS has been studied. In this research, three main issues are realized and addressed: calculation time, detailed power loss models and the communication between the on-board DAS and an off-line unit. Application of dynamic programming with heuristic state reducing rules as the optimization technique can ensure the optimality of the solution, while keeping a relative short calculation time. The heuristic state reducing rules in this study are generated based on the physical constraints of the system. The state space can be even further reduced by using a reference trajectory.
   Further, the two-stage procedure of dynamic programming ensures that there is no need for communication between the off-line unit and on-board unit. It should however be noted, that in order to improve the current DAS, it should be connected to traffic control systems and constantly updated based on adjustments to the timetable.

The Android application and the code for the dynamic programming approach are available as open source code for further research and development in the field of DAS[1].

2. *How can we increase the accuracy of power loss calculation for the problem of speed profile optimization and similar applications?* (Papers IV and V)
   Different operating conditions during different driving cycles result in change in the efficiency of the propulsion system. Each driving cycle can be realized in a domain under the graph of maximum tractive effort versus velocity. A solution to this research question is to generate a grid under the tractive effort curve, calculate the power losses for each point on the grid and generate a regression model based on the results. The regression model can subsequently be used for simulation purposes. Application of this method, in place of a constant efficiency factor, for speed profile optimization results in more energy-efficient speed profiles. In the specific case studied in this research the optimum speed profiles generated with the new loss model were 2.3% more energy-efficient on average. Further, application of this approach instead of a constant efficiency factor for the power loss calculation of a motor converter module results in significant improvements in the energy calculations.
   The experiments and evaluations with the electrical models show that the losses differ in different line voltages. It is shown that in the case of the motor converter module, one regression model with linear scaling according to the line voltage provides enough accuracy. A more accurate solution however is to generate one regression model for each line voltage.

II Energy-optimal catenary-free operation of catenary-free operated electric multiple units

1. *What are the main energy storage devices used for the catenary-free operated electric multiple units and how can they be modeled for the speed profile optimization purpose?* (Papers III and VI)
   Catenary-free operated EMUs are a recent trend in the railway industry. Thus far, only a few catenary-free EMUs have been developed. These new units are equipped with lithium-ion batteries or hydrogen fuel cells. Different models are available for monitoring the performance of these energy storage technologies. In order to select a suitable battery model for the speed profile optimization, the characteristics of the train model should also be considered. The common train model used for speed profile optimization of EMUs is the single mass point, which models the mechanical power by considering the total losses in the propulsion system. In the proposed approach presented in this research, any electrical circuit equivalent battery model that can model the battery voltage as a function of current and state of charge is suitable for use in speed profile optimization using the single mass point train model.
2. *How can a dynamic programming approach be used for speed profile optimization of catenary-free operated electric multiple units considering the characteristics of the energy storage device?* (Papers II and VI)

[1]`https://www.sics.se/projects/stream`

The dynamic programming approach used to design the DAS is adjusted for catenary-free operated EMUs by introducing state of charge as a new dimension to the state variable. Since the relation between the power at the DC link (i.e. power at the battery) and the state of charge is not linear, a new objective function is used: energy consumption from the battery in A h. Using the state of charge as a state variable and charge consumption as the objective function, characteristics of the energy consumption are considered in the problem of speed profile optimization. Both of the values of state of charge and charge consumption are calculated using the single mass point train model and mechanical power calculations.
Although the approach and models presented in this research are for the case of an EMU with a lithium-ion battery, the solution can be generalized for EMUs with other types of energy storage device using the same type of model. The results of the optimization for a certain case show a potential 31.6% reduction in energy consumption.

7. Conclusion

In sum, this thesis contributes to the problem of energy-efficient train control in two ways: application and problem formulation.

In the case of problem formulation, the thesis fills knowledge gaps regarding the problem of single train operation. According to Miyatake, in the optimization of train operation, 8 major characteristics should be considered: power losses in the grid, effects of the line voltage on the tractive effort curve, regenerative brake system, running resistance, track profile, energy storage systems, losses in the propulsion system and signaling systems (Miyatake & Ko, 2010). In this thesis, five of these issues are covered. The train model considers the regenerative brake system, running resistance and the track profile. The thesis also addresses detailed power losses in the problem of speed profile optimization. The results show that the consideration of the detailed power losses influences the optimum speed profiles and increases the energy efficiency (2.3% increase on average). Results of the optimization show a potential increase of around 28% in energy efficiency.

The thesis also examines the consideration of the energy storage device in the train configuration. The consideration of the energy storage systems in the optimization problem adds new dimensions and constraints to the original problem, which leads to new problems. The energy storage device can be considered as a stationary or on-board energy storage device. On-board energy storage devices can be used as a secondary energy source or as the sole energy source during catenary-free operation. Each of the new configurations is a separate optimization problem. In catenary-free operation, lithium-ion batteries are one of the main energy storage devices used for intercity regional trains. This thesis combines the single mass point train model with an electric circuit battery model to consider the characteristics of the battery. The electric circuit model should model the terminal voltage of the battery based on the load current and the state of charge. Results presented in this thesis show that the consideration of the battery characteristics in the problem of speed profile optimization leads to an increase in energy efficiency. Results of the optimization show an increase of around 31% in energy efficiency compared to actual driving cycles of a battery driven train.

The thesis also investigates the development of a driver advisory system based on a dynamic programming approach. Since current smartphones can provide enough data needed for a DAS, the DAS in this thesis is designed as an Android application. Although dynamic programming is an effective optimization approach, it is not efficient in terms of calculation time. The results show that the calculation time can be decreased using heuristic state reducing rules generated from the physical constraints of the system. As a result, dynamic programming can be used effectively in designing a driver advisory system as an Android application.

The driver advisory system and the optimization solutions presented here are aimed at single train operation. Therefore, they do not consider the losses in the power grid and signaling system. However, the model used in this thesis includes a constant factor for receptivity of the line during the regenerative braking mode, which can be viewed as a simplistic model of the losses in the power grid. The model could be improved by using a more sophisticated factor for line receptivity.

8. Future Directions

This research examines the problem of EETC for single train operation. The results of this thesis contribute to the problem of speed profile optimization by adding dynamic power losses and characteristics of the energy storage device during catenary-free operation. Moreover, it presents the process of designing a DAS from the mathematical formulation to the application on-board the train.

Based on the study by Panou et. al. (Panou et al., 2013), two directions of future research possibilities are suggested regarding the driver advisory system. The first direction follows the integration of the whole network into the optimization problem. This will lead to consideration of the constraints resulting from multiple train operations, which includes consideration of power losses in the grid. Moreover, the driver advisory system presented in this thesis is a stand-alone system. In order to maximize the potential energy efficiency of such a system, it should be connected to a traffic management server and be updated in real time with information regarding timetables and traffic (i.e. C-DAS). Apart from C-DAS, studies are needed to introduce automatic train operation (ATO) systems for the regional train lines.

The other direction includes aspects of the driver advisory system pertaining to human/machine interaction. This includes how the DAS should be integrated into the driver's cabin, the information that should be presented to the driver and the level of detail of this information. Another aspect of the human/machine interaction is a study of driver behavior and reaction towards the instructions from a driver advisory system.

The speed profile optimization done in this research is with the objective of minimizing energy consumption. Life and state of health of batteries however, is a key factor in application which determines the performance of the battery. In the future research in the field of speed profile optimization for catenary-free EMUs the objective of optimizing the life of the battery should also be considered. Moreover, one of the few catenary-free EMUs on the market is operating with a hybrid fuel cell-battery energy storage system. Speed profile optimization of such trains is also an interesting topic for future research.

Evaluation of the dynamic programming approach used in this thesis using a validated energy calculation software shows the potential of saving around 28% in energy consumption. For the future studies it would be interesting to study the effects of discretization of state space on the energy consumption reduction and the global optimality of the solution.

References

Acikbas, S., & Soylemez, M. T. (2008). Coasting point optimisation for mass rail transit lines using artificial neural networks and genetic algorithms. *Electric Power Applications, IET*, *2*(3), 172–182. doi: 10.1049/iet-epa:20070381

Albrecht, A., Howlett, P., Pudney, P., Vu, X., & Zhou, P. (2016, dec). The key principles of optimal train control-Part 1 Formulation of the model, strategies of optimal type, evolutionary lines, location of optimal switching points. *Transportation Research Part B: Methodological*, *94*, 482–508. doi: 10.1016/j.trb.2015.07.023

Albrecht, A. R., Howlett, P. G., Pudney, P. J., & Vu, X. (2013). Energy-efficient train control: From local convexity to global optimization and uniqueness. *Automatica*, *49*(10), 3072–3078. doi: http://dx.doi.org/10.1016/j.automatica.2013.07.008

Alstom. (2016, sep). Alstom unveils Coradia iLint hydrogen fuel cell powered train for European regional market. *Fuel Cells Bulletin*, *2016*(9), 1. doi: 10.1016/S1464-2859(16)30228-0

Baumgartner, J. (2001). *Prices and costs in the railway sector*. Institut des transports et de planification.

Becker, F., & Dammig, A. (2016, sep). Catenary free operation of light rail vehicles, Topology and operational concept. In *2016 18th european conference on power electronics and applications (epe'16 ecce europe)* (pp. 1–10). IEEE. doi: 10.1109/EPE.2016.7695286

Bocharnikov, Y. V., Tobias, A. M., & Roberts, C. (2010). Reduction of train and net energy consumption using genetic algorithms for Trajectory Optimisation. In *Iet conference on railway traction systems (rts 2010),* (pp. 1–5). doi: 10.1049/ic.2010.0038

Campillo, J., Dahlquist, E., Danilov, D. L., Ghaviha, N., Notten, P. H. L., & Zimmerman, N. (2017). Battery Technologies for Transportation Applications. In *Technologies and applications for smart charging of electric and plug-in hybrid vehicles* (pp. 151–206). Cham: Springer International Publishing. doi: 10.1007/978-3-319-43651-7_5

Chang, C. S., & Sim, S. S. (1997). Optimising train movements through coast control using genetic algorithms. *IEE Proceedings - Electric Power Applications*, *144*(1), 65–73. doi: 10.1049/ip-epa:19970797

Cheng, J., & Howlett, P. (1993). A note on the calculation of optimal strategies for the minimization of fuel consumption in the control of trains. *IEEE*

Transactions on Automatic Control,, *38*(11), 1730–1734. doi: 10.1109/9.262051

Colak, K., Czarkowski, D., & de Leon, F. (2012). Energy minimization for catenary-free mass transit systems using Particle Swarm Optimization. In *Electrical systems for aircraft, railway and ship propulsion (esars), 2012* (pp. 1–5). doi: 10.1109/esars.2012.6387414

Erchao, C., Xin, Y., & Yi, D. (2014). An energy-efficient adjustment approach in subway systems. In *2014 ieee 17th international conference on intelligent transportation systems (itsc),* (pp. 2774–2779). doi: 10.1109/itsc.2014.6958134

Fotouhi, A., Auger, D. J., Propp, K., Longo, S., & Wild, M. (2016, apr). *A review on electric vehicle battery modelling: From Lithium-ion toward Lithium-Sulphur* (Vol. 56). Pergamon. doi: 10.1016/j.rser.2015.12.009

Franke, R., Terwiesch, P., & Meyer, M. (2000). An algorithm for the optimal control of the driving of trains. In *Proceedings of the 39th ieee conference on decision and control, 2000.* (Vol. 3, pp. 2123–2128 vol.3). doi: 10.1109/cdc.2000.914108

Ghaviha, N. (2016). *Energy optimal operation of electric trains : Development of a driver advisory system* (No. 237). Mälardalen University.

Ghaviha, N., Bohlin, M., & Dahlquist, E. (2016, jun). Speed profile optimization of an electric train with on-board energy storage and continuous tractive effort. In *2016 international symposium on power electronics, electrical drives, automation and motion (speedam)* (pp. 639–644). IEEE. doi: 10.1109/SPEEDAM.2016.7525913

Ghaviha, N., Bohlin, M., Holmberg, C., Dahlquist, E., Skoglund, R., & Jonasson, D. (2017, dec). A driver advisory system with dynamic losses for passenger electric multiple units. *Transportation Research Part C: Emerging Technologies*, *85*, 111–130. doi: 10.1016/j.trc.2017.09.010

Ghaviha, N., Bohlin, M., Wallin, F., & Dahlquist, E. (2015). Optimal control of an emu using dynamic programming and tractive effort as the control variable. In *Proceedings of the 56th conference on simulation and modelling (sims 56), october, 7-9, 2015, linköping university, sweden* (p. 377-382). Linköping University Electronic Press, Linköpings universitet.

Ghaviha, N., Campillo, J., Bohlin, M., & Dahlquist, E. (2017, may). Review of Application of Energy Storage Devices in Railway Transportation. *Energy Procedia*, *105*, 4561–4568. doi: 10.1016/j.egypro.2017.03.980

Ghaviha, N., Holmberg, C., Bohlin, M., & Dahlquist, E. (2017, dec). Modeling of Losses in the Motor Converter Module of Electric Multiple Units for Dynamic Simulation Purposes. *Energy Procedia*, *142*, 2303–2309. doi: 10.1016/j.egypro.2017.12.633

Gkortzas, P. (2013). *Study on optimal train movement for minimum energy consumption* (Unpublished master's thesis). Mälardalen University, School of Innovation, Design and Engineering.

Haahr, J. T., Pisinger, D., & Sabbaghian, M. (2017). A dynamic programming approach for optimizing train speed profiles with speed restrictions and passage points. *Transportation Research Part B: Methodological*, *99*, 167–182. doi: 10.1016/j.trb.2016.12.016

Hellström, E., Åslund, J., & Nielsen, L. (2010). Design of an efficient algorithm for fuel-optimal look-ahead control. *Control Engineering Practice*, *18*(11), 1318–1327. doi: http://dx.doi.org/10.1016/j.conengprac.2009.12.008

Hoffrichter, A., Miller, A. R., Hillmansen, S., & Roberts, C. (2012, jan). Well-to-wheel analysis for electric, diesel and hydrogen traction for railways. *Transportation Research Part D: Transport and Environment*, *17*(1), 28–34. doi: 10.1016/J.TRD.2011.09.002

Howlett, P. (2000). The Optimal Control of a Train. *Annals of Operations Research*, *98*(1-4), 65–87. doi: 10.1023/a:1019235819716

Hui-Jen, C., Chao-Shun, C., Chia-Hung, L., Ching-Ho, H., & Chin-Yin, H. (2008). Design of optimal coasting speed for saving social cost in Mass Rapid Transit systems. In *Third international conference on electric utility deregulation and restructuring and power technologies, 2008. drpt 2008.* (pp. 2833–2839). doi: 10.1109/drpt.2008.4523892

Ichikawa, K. (1968). Application of Optimization Theory for Bounded State Variable Problems to the Operation of Train. *Bulletin of JSME*, *11*(47), 857–865. doi: 10.1299/jsme1958.11.857

IEA & UIC. (2016). *Railway handbook 2016. Energy consumption and CO2 emissions* (Tech. Rep.). International Energy Agency, Union of Railways.

IEA & UIC. (2017). *Railway handbook 2017. Energy consumption and CO2 emissions* (Tech. Rep.). International Energy Agency, Union of Railways.

Jih-Wen, S., & Wei-Song, L. (2012). Energy-Saving Automatic Train Regulation Using Dual Heuristic Programming. *IEEE Transactions on Vehicular Technology,*, *61*(4), 1503–1514. doi: 10.1109/tvt.2012.2187225

Johnson, V. H. (2002, aug). Battery performance models in ADVISOR. In *Journal of power sources* (Vol. 110, pp. 321–329). Elsevier. doi: 10.1016/S0378-7753(02)00194-5

Ko, H., Koseki, T., & Miyatake, M. (2004). Application of dynamic programming to optimization of running profile of a train. *Computers in railways IX*, 103–112.

Kono, Y., Shiraki, N., Yokoyama, H., & Furuta, R. (2014). Catenary and storage battery hybrid system for electric railcar series EV-E301. In *2014 international power electronics conference (ipec-hiroshima 2014 - ecce-asia),* (pp. 2120–2125). doi: 10.1109/ipec.2014.6869881

Lechelle, S. A., & Mouneimne, Z. S. (2010). OptiDrive: A practical approach for the calculation of energy-optimised operating speed profiles. In *Iet conference on railway traction systems (rts 2010)* (pp. 1–8). doi: 10

.1049/ic.2010.0029
Liu, R., & Golovitcher, I. M. (2003). Energy-efficient operation of rail vehicles. *Transportation Research Part A: Policy and Practice*, *37*(10), 917–932. doi: http://dx.doi.org/10.1016/j.tra.2003.07.001
Menon, P., & Park, S. (2016, jan). Dynamics and control technologies in air traffic management. *Annual Reviews in Control*, *42*, 271–284. doi: 10.1016/j.arcontrol.2016.09.012
Miyatake, M., & Ko, H. (2007a). Numerical analyses of minimum energy operation of multiple trains under DC power feeding circuit. In *2007 european conference on power electronics and applications,* (pp. 1–10). doi: 10.1109/epe.2007.4417260
Miyatake, M., & Ko, H. (2007b). Numerical Optimization of Speed Profiles of Inverter Trains Considering DC Feeding Circuit. In *Power conversion conference - nagoya, 2007. pcc '07* (pp. 336–341). doi: 10.1109/pccon.2007.372989
Miyatake, M., & Ko, H. (2010). Optimization of Train Speed Profile for Minimum Energy Consumption. *IEEJ Transactions on Electrical and Electronic Engineering*, *5*(3), 263–269. doi: 10.1002/tee.20528
Miyatake, M., & Matsuda, K. (2008). Optimal speed and charge/discharge control of a train with onboard energy storage devices for minimum energy operation. In *International symposium on power electronics, electrical drives, automation and motion, 2008. speedam 2008.* (pp. 1211–1216). doi: 10.1109/speedham.2008.4581323
Mousavi G., S., & Nikdel, M. (2014, apr). Various battery models for various simulation studies and applications. *Renewable and Sustainable Energy Reviews*, *32*, 477–485. doi: 10.1016/j.rser.2014.01.048
Noda, Y., & Miyatake, M. (2016, nov). Methodology to apply dynamic programming to the energy-efficient driving technique of lithium-ion battery trains. In *2016 international conference on electrical systems for aircraft, railway, ship propulsion and road vehicles & international transportation electrification conference (esars-itec)* (pp. 1–6). IEEE. doi: 10.1109/ESARS-ITEC.2016.7841337
Panou, K., Tzieropoulos, P., & Emery, D. (2013). Railway driver advice systems: Evaluation of methods, tools and systems. *Journal of Rail Transport Planning & Management*, *3*(4), 150–162. doi: http://dx.doi.org/10.1016/j.jrtpm.2013.10.005
Pengling Wang. (2017). *Train Trajectory Optimization Methods for Energy-Efficient Railway Operations* (Doctoral dissertation, Delft University of Technology). doi: 10.4233/uuid:ce04a07d-89fc-470a-9d1a-b6fae9182dae
Puleston, P., Valenciaga, F., Battaiotto, P., & Mantz, R. (2000, nov). Passivity/sliding mode control of a stand-alone hybrid generation system. *IEE Proceedings - Control Theory and Applications*, *147*(6), 680–686. doi: 10.1049/ip-cta:20000803

Rivera-Barrera, J., Muñoz-Galeano, N., & Sarmiento-Maldonado, H. (2017, nov). SoC Estimation for Lithium-ion Batteries: Review and Future Challenges. *Electronics*, *6*(4), 102. doi: 10.3390/electronics6040102

Scheepmaker, G. M., Goverde, R. M., & Kroon, L. G. (2017, mar). Review of energy-efficient train control and timetabling. *European Journal of Operational Research*, *257*(2), 355–376. doi: 10.1016/j.ejor.2016.09.044

Shafiei, A., Momeni, A., & Williamson, S. S. (2011, sep). Battery modeling approaches and management techniques for Plug-in Hybrid Electric Vehicles. In *2011 ieee vehicle power and propulsion conference* (pp. 1–5). IEEE. doi: 10.1109/VPPC.2011.6043191

Sheu, J. W., & Lin, W. S. (2011). Automatic train regulation with energy saving using dual heuristic programming. *Electrical Systems in Transportation, IET*, *1*(2), 80–89. doi: 10.1049/iet-est.2010.0074

Shibuya, H., & Kondo, K. (2011, sep). Designing Methods of Capacitance and Control System for a Diesel Engine and EDLC Hybrid Powered Railway Traction System. *IEEE Transactions on Industrial Electronics*, *58*(9), 4232–4240. doi: 10.1109/TIE.2010.2100332

Shuai, S., Xiang, L., Tao, T., & Ziyou, G. (2013). A Subway Train Timetable Optimization Approach Based on Energy-Efficient Operation Strategy. *Intelligent Transportation Systems, IEEE Transactions on*, *14*(2), 883–893. doi: 10.1109/tits.2013.2244885

Tang, H., Wang, Q., & Pe, C. T. D. (2014). Optimizing Train Speed Profiles To Improve Regeneration Efficiency of Transit Operations. In *Proceedings of the 2014 joint rail conference* (pp. 1–8).

Tremblay, O., & Dessaint, L.-A. (2009). Experimental Validation of a Battery Dynamic Model for EV Applications. *World Electric Vehicle Journal*, *3*.

Tremblay, O., Dessaint, L.-A., & Dekkiche, A.-I. (2007, sep). A Generic Battery Model for the Dynamic Simulation of Hybrid Electric Vehicles. In *2007 ieee vehicle power and propulsion conference* (pp. 284–289). IEEE. doi: 10.1109/VPPC.2007.4544139

Tsukahara, K., & Kondo, K. (2013). A study on methods to design and select energy storage devices for Fuel Cell hybrid powered railway vehicles. In *39th annual conference of the ieee industrial electronics society, iecon 2013* (pp. 4534–4539). doi: 10.1109/iecon.2013.6699866

Wang, P., & Goverde, R. M. (2016). Multiple-phase train trajectory optimization with signalling and operational constraints. *Transportation Research Part C: Emerging Technologies*, *69*, 255–275. doi: 10.1016/j.trc.2016.06.008

Wang, P., & Goverde, R. M. (2017a, jun). Development of a train driver advisory system: ETO. In *5th ieee international conference on models and technologies for intelligent transportation systems, mt-its 2017 - proceedings* (pp. 140–145). IEEE. doi: 10.1109/MTITS.2017.8005654

Wang, P., & Goverde, R. M. (2017b, nov). Multi-train trajectory optimization for energy efficiency and delay recovery on single-track railway lines. *Transportation Research Part B: Methodological*, *105*, 340–361. doi: 10.1016/j.trb.2017.09.012

Wong , K. K., & Ho, T. K. (2004). Dynamic coast control of train movement with genetic algorithm. *International Journal of Systems Science*, *35*(13-14), 835–846. doi: 10.1080/00207720412331203633

Wong, K. K., & Ho, T. K. (2004). Coast control for mass rapid transit railways with searching methods. *IEE Proceedings - Electric Power Applications,*, *151*(3), 365–376. doi: 10.1049/ip-epa:20040346

Xu, L., & Chen, D. (2011, oct). Control and Operation of a DC Microgrid With Variable Generation and Energy Storage. *IEEE Transactions on Power Delivery*, *26*(4), 2513–2522. doi: 10.1109/TPWRD.2011.2158456

Yang, L., Liden, T., & Leander, P. (2013, aug). Achieving energy-efficiency and on-time performance with Driver Advisory Systems. In *2013 ieee international conference on intelligent rail transportation proceedings* (pp. 13–18). IEEE. doi: 10.1109/ICIRT.2013.6696260

Yang, X., Chen, A., Li, X., Ning, B., & Tang, T. (2015). An energy-efficient scheduling approach to improve the utilization of regenerative energy for metro systems. *Transportation Research Part C: Emerging Technologies*, *57*, 13–29. doi: 10.1016/j.trc.2015.05.002

Yasunobu, S., Miyamoto, S., & Ihara, H. (1983). A Fuzzy Control for Train Automatic Stop Control. *Transactions of the Society of Instrument and Control Engineers*, *19*(11), 873–880. doi: 10.9746/sicetr1965.19.873

Yin, J., Chen, D., & Li, L. (2014, dec). Intelligent Train Operation Algorithms for Subway by Expert System and Reinforcement Learning. *IEEE Transactions on Intelligent Transportation Systems*, *15*(6), 2561–2571. doi: 10.1109/TITS.2014.2320757

Yoneyama, T., Yamamoto, T., Kondo, K., Furuya, T., & Ogawa, K. (2007). Fuel cell powered railway vehicle and experimental test results. In *2007 european conference on power electronics and applications* (pp. 1–10). IEEE. doi: 10.1109/EPE.2007.4417299

Zhang, D., Shi, J., Zhao, H., & Wu, T. (2017, oct). Loss characteristic analysis of small and medium-sized induction motors fed by PWM inverter based on the experiment measurements. In *Iecon 2017 - 43rd annual conference of the ieee industrial electronics society* (Vol. 2017-Janua, pp. 2053–2058). IEEE. doi: 10.1109/IECON.2017.8216345

Zhu, H., Sun, X., Chen, L., Gao, S., & Dong, H. (2016). *Analysis and design of Driver Advisory System (DAS) for energy-efficient train operation with real-time information.* doi: 10.1109/ICIRT.2016.7588717